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From Financial Accounting to Sustainability: A Data-Driven Hybrid Life Cycle Assessment Framework for Decarbonization and Decision-Making in Corporate Procurement

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Résumés en français et en anglais

De la comptabilité financière à la durabilité : un cadre d'analyse du cycle de vie hybride fondé sur les données pour la décarbonation et la prise de décision dans les achats des entreprises

Résumé

En réponse aux impératifs environnementaux et sociaux croissants, les entreprises sont de plus en plus incitées à prendre en compte les impacts de durabilité tout au long de leurs chaînes de valeur. Les émissions indirectes de catégorie 3 (Scope 3), telles que définies par le GHG Protocol, notamment celles liées aux achats, représentent une part significative de l'empreinte carbone des entreprises, tout en demeurant les plus complexes à quantifier et à évaluer. Cette thèse explore les défis systémiques, méthodologiques et organisationnels liés à la comptabilisation carbone des achats de catégorie 3, et propose un cadre hybride et semi-automatisé destiné à renforcer la précision, la couverture et la pertinence des évaluations.

La première contribution consiste en une revue critique des méthodes existantes de comptabilité carbone. L'Analyse du Cycle de Vie (ACV) fournit des données détaillées au niveau produit, tandis que les modèles d'Entrées-Sorties enrichis par des données environnementales (EEIO) offrent une couverture macroéconomique plus large. Toutefois, ces approches présentent des limites structurelles lorsqu'elles sont utilisées isolément. En s'appuyant sur l'Analyse de la Durabilité du Cycle de Vie (ADCV), ce travail développe une approche hybride intégrée combinant des indicateurs environnementaux, des paramètres économiques et des indicateurs sociaux, élargissant ainsi l'évaluation de la durabilité au-delà du seul carbone. La revue intègre également les méthodes de comptabilité par activités (ABC) et de comptabilité par activités pilotée par le temps (TD-ABC), en soulignant leur potentiel pour allouer les coûts et les impacts, notamment lorsqu'elles sont couplées à l'ACV environnementale ou sociale. Une attention particulière est accordée au rôle croissant de la digitalisation et de l'automatisation dans la collecte et le traitement des données, permettant une meilleure exploitation des données d'achats dans les modèles de comptabilité durable. En cartographiant les convergences entre systèmes comptables classiques et outils d'évaluation de la durabilité, cette partie jette les bases de modèles intégrés, opérationnels et évolutifs répondant aux exigences des nouvelles normes ESG.

La deuxième partie propose un diagnostic systémique des enjeux de fiabilité dans la comptabilisation des émissions Scope 3. À travers une méthode mixte combinant revue systématique de la littérature, enquête d'experts et analyse structurelle MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement), la recherche identifie des défis interdépendants classés selon le cadre des 6M : Main-d'œuvre, Méthode, Matière, Machine, Mesure et Management. Ces résultats alimentent

une feuille de route stratégique fondée sur le tableau de bord prospectif de la durabilité (Sustainability Balanced Scorecard, SBSC), formulant des recommandations concrètes pour intégrer la qualité des données et la performance durable dans la gouvernance des achats. Un outil de hiérarchisation croisée et une analyse par catégorie de métier permettent de cibler les leviers d'action prioritaires.

La troisième et principale partie présente le développement d'un modèle hybride systématique à paliers (Systematic Tiered Hybrid LCA), adapté aux secteurs industriels et de services en France. Ce modèle combine des données issues des bases EEIO, des ACV processus, et des déclarations fournisseurs. Un algorithme semi-automatisé sélectionne dynamiquement les données les plus pertinentes (monétaires ou physiques), selon les caractéristiques de chaque ligne d'achat. Le modèle fonctionne au niveau sectoriel (via les données financières et les coefficients EEIO) ou au niveau produit (via des quantités physiques et des facteurs d'émission spécifiques), assurant à la fois précision et évolutivité. Son architecture flexible permet de combler les lacunes de données, d'améliorer la résolution des résultats, et d'assurer la conformité aux exigences réglementaires et organisationnelles. Ce modèle a été validé en partenariat avec Eiffage, acteur majeur du BTP en France, démontrant sa faisabilité pratique et sa valeur ajoutée pour les stratégies de décarbonation des entreprises.

La quatrième partie porte sur l'intégration des dimensions sociales dans l'évaluation des achats et leur articulation avec des méthodes de comptabilité des coûts. Tout d'abord, le modèle monétaire top-down, initialement conçu pour l'évaluation environnementale, est étendu aux impacts sociaux à travers l'intégration de la base PSILCA. Un flux de travail semi-automatisé permet d'associer les dépenses d'achats à des facteurs de risque social propres à chaque secteur, fournissant ainsi un cadre d'évaluation à la fois évolutif, systématique et cohérent pour l'analyse des impacts sociaux au sein des portefeuilles d'achats. Ce développement reflète le même principe d'automatisation et de structuration logique que celui appliqué aux impacts environnementaux. Ensuite, une modélisation distincte explore l'intégration de la méthode TD-ABC (Time-Driven Activity-Based Costing) avec l'ACV sociale. Ce cadre méthodologique permet de quantifier la capacité inutilisée des ressources et d'allouer les coûts ainsi que les impacts sociaux à l'aide d'inducteurs temporels, tant au niveau des activités qu'à celui des produits. Il est appliqué et validé à travers une étude de cas illustrative dans le secteur de l'emballage, démontrant comment les estimations de temps et les taux de coût de capacité peuvent être utilisés pour retracer les risques sociaux associés à des produits et activités spécifiques. Ensemble, ces deux modèles renforcent l'analyse multidimensionnelle des décisions d'achat, permettant d'identifier plus précisément les arbitrages entre performance financière et responsabilité sociétale, et de soutenir une allocation stratégique des ressources vers une durabilité pleinement intégrée.

Sur le plan théorique, cette thèse fait progresser la comptabilité hybride de la durabilité et l'opérationnalisation de l'ADCV dans les contextes d'achats. Sur le plan pratique, elle propose un cadre

reproductible, adaptable et digitalisé permettant aux entreprises de répondre aux exigences réglementaires croissantes et d'intégrer les responsabilités environnementales et sociales dans leurs décisions d'achats. En articulant la pensée en cycle de vie, l'automatisation numérique et l'usage d'indicateurs multidimensionnels, ce travail propose une approche systémique de la gouvernance durable, encourageant une éthique de responsabilité partagée et une prise de décision fondée sur une vision intégrée. Plus largement, il soutient l'innovation fondée sur les données ainsi que la transformation de la fonction achats, en la faisant évoluer d'un rôle centré sur la maîtrise des coûts vers un levier stratégique de durabilité et de résilience, au service de la transition vers une société neutre en carbone.

Mots clés: **Analyse du cycle de vie hybride (ACV hybride), Analyse de la durabilité du cycle de vie (ADCV), Analyse de Scope 3, Achats responsables, Décarbonation, GHG Protocol, Automatisation des données**

From Financial Accounting to Sustainability: A Data-Driven Hybrid Life Cycle Assessment Framework for Decarbonization and Decision-Making in Corporate Procurement

Abstract

In response to growing environmental and social imperatives, companies are increasingly encouraged to address sustainability impacts across their value chains. Indirect Scope 3 emissions, as categorized by the GHG Protocol and notably those linked to procurement, account for a substantial portion of corporate carbon footprints, while posing significant challenges in terms of measurement and evaluation. This dissertation explores the systemic, methodological, and organizational challenges of Scope 3 procurement-related carbon accounting and proposes a hybrid, semi-automated framework to improve precision, coverage, and relevance.

The first contribution is a critical review of existing carbon accounting methods. While process-based Life Cycle Assessment (LCA) provides detailed product-level data, and Environmentally Extended Input-Output (EEIO) models offer broad economy-wide coverage, both approaches face structural limitations when applied independently. Drawing on Life Cycle Sustainability Assessment (LCSA), this work develops an integrated approach combining environmental indicators, economic parameters, and social metrics, expanding sustainability assessment beyond carbon. The review also includes Activity-Based Costing (ABC) and Time-Driven ABC (TD-ABC) methods, highlighting their potential to support cost and impact allocation, especially when integrated with LCA or Social LCA frameworks. Special attention is paid to the growing role of digitalization and automation technologies in streamlining data collection and processing, enabling the use of procurement data in sustainability accounting models. By mapping the convergence between traditional accounting systems and sustainability assessment

tools, this contribution lays the foundation for integrated, operational, and scalable models that reflect the evolving demands of ESG reporting. This multidimensional approach aligns with emerging sustainability reporting standards and academic frameworks.

The second contribution is a systemic diagnosis of reliability challenges in Scope 3 accounting. Using a mixed-method design, including a systematic literature review, expert survey, and MICMAC structural analysis (Cross-Impact Matrix Multiplication Applied to Classification), this research identifies interdependent challenges and classifies them within the 6M framework: Man, Method, Material, Machine, Measurement, and Management. These insights inform a strategic roadmap based on the Sustainability Balanced Scorecard (SBSC), providing actionable recommendations to embed data quality and sustainability performance into procurement governance.

The third and main contribution is the development of a Systematic Tiered Hybrid LCA model, tailored to industrial and service sectors in France. This model integrates EEIO data, process-based LCA data, and supplier-specific disclosures. A rule-based, semi-automated algorithm dynamically selects the most robust available data, monetary or physical, depending on procurement line-item characteristics. The model operates at the sector level using financial data and EEIO coefficients, or at the product level using physical quantities and process-specific emission factors. This ensures both scalability and accuracy. The flexible architecture reduces data gaps, improves resolution, and ensures alignment with regulatory and organizational requirements. The model was validated with Eiffage, a major player in the French construction sector, confirming its practical feasibility and relevance for corporate decarbonization strategies.

The fourth contribution focuses on the integration of social dimensions into procurement assessment and their alignment with cost accounting methods. The model goes beyond environmental metrics by incorporating social indicators. First, the top-down monetary model, previously used for environmental impact calculation, is expanded to include social indicators through the integration of the PSILCA database. A semi-automated workflow enables the mapping of procurement expenditure to sector-level social risk factors, providing a scalable and consistent method to assess social impacts across large purchasing portfolios. This mirrors the logic used in environmental modeling and ensures structural coherence between environmental and social evaluations. Second, a modeling stream explores the integration of Time-Driven Activity-Based Costing (TD-ABC) with Social Life Cycle Assessment (S-LCA). This framework quantifies unused resource capacity and enables the allocation of costs and social impacts, guided by time-based drivers, at both the activity and product levels. It is applied and validated through an illustrative case study in the packaging sector, demonstrating how time estimations and capacity cost rates can be used to trace social risks to specific products and activities. Together, these two models enhance the multidimensional assessment of procurement

decisions, enabling a more precise understanding of trade-offs between financial performance and social responsibility, and supporting more informed, sustainability-aligned resource allocation.

Theoretically, the dissertation advances hybrid sustainability accounting and operationalizes LCSA in procurement contexts. Practically, it proposes a scalable, reproducible framework to help companies comply with evolving regulations and integrate environmental and social responsibility into procurement decisions. By combining life cycle thinking, digital automation, and multidimensional indicators, this work promotes a systemic, accountable approach to sustainable governance. More broadly, it supports data-driven innovation and contributes to the transformation of procurement from a function primarily focused on cost control to a strategic driver of sustainability and resilience, aligned with the transition toward a carbon-neutral society.

Keywords: Hybrid Life Cycle Assessment (Hybrid LCA), Life Cycle Sustainability Assessment (LCSA), Scope 3, Sustainable Procurement, Decarbonization, GHG Protocol, Data Automation

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Acknowledgments

I don't know if someone will ever read these lines. Maybe they will simply turn the page, looking for results and citations. But if someone does stop here, even for a moment, I want them to feel the truth behind this work.

This thesis is not just a compilation of chapters, references, and data. It is a testimony. A testimony of effort, of hope, of pain, and of growth. It represents three years of my life, a journey filled with academic learning, yes, but also filled with human experience. And that, perhaps, is the most important part.

Over these three years, I attended conferences, wrote papers, joined training sessions, worked in teams, collaborated, exchanged ideas, everything a researcher is supposed to do. But that's only one side of the story.

There were also sleepless nights and long days when the weight felt unbearable. There were times when I couldn't find the answers, when my health suffered, when fatigue turned into silence and insomnia turned into despair. There were moments of chaos, when I lost my rhythm, my focus, even my confidence. Times when giving up felt like the easier option. But I didn't. I held on. Sometimes barely. But I did.

There were tears no one saw, victories no one noticed, and quiet moments of courage that kept me going.

This thesis carries all of that, it carries me. And for that, I owe so much thanks.

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This thesis is more than a scientific document. It is a mirror of my journey, of every struggle and every small triumph. It holds my doubts, my persistence, and the faces of those who helped me become who I am today.

From the bottom of my heart: Thank you.

Eng. (soon to be Dr.) Widiene Essouid

Closing the chapter of science… and taking flight to celebrate love.

Written from a plane, on the way to my wedding, with gratitude and a full heart.

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Preface

This doctoral thesis is the result of a collaborative and interdisciplinary effort, carried out between 2022 and 2025 as part of a multi-partner research project. It brings together expertise from management sciences, environmental assessment, and digital innovation. On the academic side, it reflects a convergence between IRGO (Institut de Recherche en Gestion des Organisations) and the CyVi research group from the Institute of Molecular Sciences (ISM), within the University of Bordeaux. The ambition behind this work was to bridge economic, environmental and social indicators into a unified framework for sustainability accounting, using procurement as a strategic entry point, not only for reporting, but also for innovation and decision-making.

The research was co-supervised by Professor Stéphane Trébucq and Professor Guido Sonnemann, whose complementary expertise in financial accounting and Life Cycle Sustainability Assessment has been instrumental in shaping this hybrid approach. The thesis was further supported by industrial partner : Eiffage, a major actor in the construction sector in France. This collaboration, formalized in 2024, provided a unique opportunity to apply and validate the proposed hybrid model in a real-world procurement context, enabling the integration of supplier-specific data into strategic decision-making tools.

This thesis builds on, and contributes to, the ongoing integration of environmental and social criteria into management systems. It proposes a semi-automated hybrid framework that draws from Life Cycle Assessment (LCA), Environmentally Extended Input-Output (EEIO), and supplier disclosures to support sustainability-driven procurement and corporate decision-making. The model is further extended to incorporate social dimensions, enabling a more holistic assessment of supply chain impacts. Additionally, it integrates cost accounting systems with Social Life Cycle Assessment (SLCA), providing a coherent and unified framework that aligns social sustainability metrics with financial data. Several publications and conference contributions have emerged from this research, attesting to its relevance in both academic and practical contexts.

Conference Contributions:

Oral Communications

1. Essouid, W. et al. (2025). La CSRD et les ESRS : avancée ou recul en matière de gouvernance de la durabilité ?. Conférence Internationale de la Gouvernance et de la Durabilité 2025, Hammamet, **Tunisia**. https://hal.science/hal-05364388
2. Essouid, W. et al. (2025). Innovation durable ou simple reporting ? État de l'art de l'évaluation des émissions de carbone liées aux achats organisationnels. Congrès Management du Cycle de Vie (MCV) 2025, Bordeaux, **France**. https://hal.science/hal-5380619

3. Essouid, W. et al. (2025). Améliorer la comptabilité des émissions du Scope 3 Amont grâce à des systèmes d'intégration de données automatisés : Une étude de cas sur le Béton Prêt à l'Emploi mis en œuvre par Eiffage. Congrès Management du Cycle de Vie (MCV) 2025, Bordeaux, **France**. https://hal.science/hal-05380626
4. Essouid, W. et al. (2025). Sustainable Innovation or Merely Reporting? State of the Art of Assessing Scope 3 Emissions in Organizational Procurement. 12th International Conference on Life Cycle Management, Palermo, **Italy**. https://hal.science/hal-05310546
5. Essouid, W. et al. (2024). Comment mieux intégrer les impacts sociaux aux outils d'aide à la décision? Atelier Thématique Annuel EcoSD 2024, Paris, **France**. https://hal.science/hal-04869209/
6. Essouid, W. et al. (2024). Comptabilité TD-ABC et Analyse Sociale de Cycle de Vie: Une analyse de leur intégration possible au travers d'une étude de cas. MCV 2024: Management Du Cycle de Vie, Lille, **France**. https://hal.science/hal-04869208/
7. Essouid, W. et al. (2024). Unveiling the Synergy: Integration of Time-Driven Activity Based Costing with Social Life Cycle Assessment. 9th International Conference of Social Life Cycle Assessment, Curitiba, **Brazil**. https://hal.science/hal-04710388

Posters

1. Essouid, W. et al. (2025). De l'intuition à la stratégie : analyser et structurer les défis du Scope 3 in Congrès Management du Cycle de Vie (MCV) 2025, Bordeaux, **France**. https://hal.science/hal-05380632
2. Essouid, W., Loubet, P., Sonnemann, G., & Trebucq, S. (2023). Integrating accounting data with Scope 3 emissions data for valorizing LCA results in a Life Cycle Management perspective. LCM 2023, Lille, **France**. https://hal.science/hal-04710440
3. Essouid, W., Loubet, P., Sonnemann, G., & Trébucq, S. (2023). Integrating accounting data with Scope 3 emissions data for valorizing LCA results in the Energy Sector. University of Tampere, **Finland**. https://hal.science/hal-05185438

Publications:

Book Chapters

1. *(Published):* Essouid, W. & Trébucq, S. (2025). Carbon Resilience at the Heart of Responsible Procurement: Illustration and Perspectives. In MANAGER LES RÉSILIENCES, Éditions EMS. (Original title: « La Résilience Carbone au Cœur des Achats Responsables »)
2. *(Accepted):* Essouid, W., Zobel, J., Loubet, P., Trébucq, S., Köhler, S., et al. (2025). Sustainable Innovation or Merely Reporting? State of The Art of Assessing Scope 3 Emissions of Organizational Procurement. In LCM 2025 Proceedings (Springer).

3. *(Accepted):* Essouid, W., Bouillass, G., Trébucq, S., Loubet, P., Sonnemann, G., De la comptabilité des coûts à la soutenabilité sociale: un modèle intégré pour les entreprises. In « Analyse sociale de cycle de vie:enjeux,théorie et pratiques », Paris, Presses des Mines, collection Énergie et développement durable, 2026.

Articles

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2. *(Second Round of Review):* Essouid, W., Salem,H., Trébucq, S., Loubet, P., Sonnemann, G., Improving Scope 3 Procurement Emissions Accounting: A Strategic Approach Using MICMAC and the Sustainability Balanced Scorecard. (Journal : Corporate Social Responsibility and Environmental Management).
3. *(First Round of Review):* Essouid, W., Trébucq, S., Sonnemann, G. La CSRD et les ESRS : avancée ou recul en matière de gouvernance de la durabilité ? (Journal : Management & Prospective)
4. *(Draft Finalization) :* Essouid, W., et al. A Systematic Hybrid Approach to Scope 3 Procurement Emissions: Supporting Innovation and Decision-Making.
5. *(Draft Finalization)* : Essouid, W., et al. Integrating Social and Environmental Intensities into Procurement-Based LCSA: A Sector-Level Framework for France.
6. *(Draft Finalization)* Essouid, W., et al. Automated Data Processing for Procurement and Upstream Scope 3 Emissions Accounting: Evidence from a Ready-Mixed Concrete Case Study

This work would not have been possible without the combined efforts of my academic advisors, project collaborators, and the organizations who believed in the importance of moving toward more responsible and data-informed management practices. While the research focuses on methods and models, it is, above all, a testament to the potential of interdisciplinary dialogue in solving today's complex sustainability challenges.

1| General Introduction

This chapter introduces the context and motivation for the thesis, emphasizing the urgency of decarbonization and the strategic role of procurement in driving climate action. While carbon reduction remains a critical goal, the chapter highlights the need to go beyond carbon and adopt a broader sustainability perspective that encompasses other environmental impacts (e.g., resource use, pollution) as well as social dimensions such as labor rights, human well-being, and equity. It underscores the current limitations in integrating these broader environmental and social criteria into procurement practices and accounting systems, pointing to a significant gap this research aims to address. The chapter concludes by outlining the research interest, questions, objectives and structure of the thesis.

A summary version of this chapter, authored by Essouid and Trébucq, has been accepted for publication in the collective volume MANAGER LES RÉSILIENCES (Éditions EMS), under the title:
(FR) « La Résilience Carbone au Cœur des Achats Responsables: Illustration et Perspectives »
(ENG) « Carbon Resilience at the Heart of Responsible Procurement: Illustration and Perspectives »

I. Context and Research Motivation

As the global economy confronts mounting climate risks, the transition to a low-carbon model has become a strategic imperative for both businesses and policymakers (Iacobuţă et al., 2021). While efforts to limit direct (Scope 1) and energy-related (Scope 2) emissions have advanced in many sectors (Dragomir et al., 2023; Issa Zadeh et al., 2023), the largest share of corporate emissions often lies hidden in supply chains, categorized as Scope 3 (WRI and WBCSD, 2013). Because these emissions fall outside a company's direct control, they are notoriously difficult to manage. Procurement, a key driver of value chain activities, has therefore emerged as a powerful but underutilized lever for corporate decarbonization (Vieira et al., 2024).

Transforming procurement into a vehicle for climate action presents critical challenges (Hettler and Graf-Vlachy, 2024). Organizations often face fragmented supply chains, inconsistent or unavailable supplier-specific data, and a lack of standardized methods to track environmental and social impacts (Stridsland et al., 2023a). Although frameworks such as the GHG Protocol and ISO 14064 have laid important groundwork for emissions accounting (ISO 14064, 2018; WRI and WBCSD, 2011a), they fall short for the complex realities of Scope 3 tracking, particularly when carbon data is disconnected from procurement decisions.

Simultaneously, there is a broader shift toward integrating sustainability into corporate accounting and decision-making (Oliveira et al., 2025). Emerging extra-financial accounting frameworks increasingly call on firms to align environmental and social performance with financial and operational strategies (Mahmoudian et al., 2021). This evolution is reinforced by new regulations, most notably the European Union's Corporate Sustainability Reporting Directive (CSRD), which impose stricter obligations for transparent, auditable, and holistic ESG (Environment, Social and Governance) disclosures across supply chains (European Commission, 2023a).

Procurement and Scope 3 Decarbonization: From Measurement to Mandate

To manage greenhouse gas (GHG) emissions effectively, companies rely on standardized frameworks for quantification, reporting, and planning. Two of the most widely recognized frameworks are the GHG Protocol (WRI and WBCSD, 2011a) and ISO 14064 (2018), both serve as foundational and authoritative standards for emissions accounting across corporate operations and supply chains, though they differ in purpose and classification of GHG emissions.

The GHG Protocol, developed by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD), provides a structured, scope-based method for classifying greenhouse gas emissions. It defines three scopes: Scope 1 for direct emissions from owned or controlled sources; Scope 2 for indirect emissions from purchased energy; and Scope 3 for all other indirect emissions across the value chain, including upstream and downstream activities. Scope 3 is further divided into 15 categories to enhance transparency and comparability (WRI and WBCSD, 2013). The GHG Protocol is widely used for corporate carbon footprinting and voluntary sustainability reporting, offering detailed methodologies aligned with initiatives such as the Global Reporting Initiative (GRI, 2023), the Science-Based Targets initiative (SBTi, 2023), and the Carbon Disclosure Project (CDP, 2023), with 97% of S&P 500 CDP reporters using it.

In contrast, ISO 14064, originally published in 2006 by the International Organization for Standardization and updated in 2018, offers a flexible, category-based framework for organizational and project-level GHG accounting. It classifies emissions into six categories, covering both direct and various types of indirect emissions: (1) direct GHG emissions, (2) energy indirect GHG emissions, (3) indirect GHG emissions from transport, (4) indirect GHG emissions from products used by the organization, (5) indirect GHG emissions associated with the use of products, and (6) other indirect GHG emissions. ISO 14064 is particularly suited for regulatory reporting, third-party verification, and emissions trading, and is recognized by institutions such as the United Nations Framework Convention on Climate Change (UNFCCC, 2025). It is especially preferred in contexts where formal verification and regulatory compliance are critical.

Despite these differences, both frameworks underscore the importance of accurate emissions tracking as a foundation for climate action. Yet, measurement alone does not reduce emissions. Given that Scope 3 emissions, especially from purchased goods and services, and logistics, typically dominate corporate footprints, procurement becomes a key decarbonization lever (SBTi, 2024a). This makes supplier engagement and low-carbon sourcing central to any meaningful emissions reduction strategy.

Given procurement's influence over emissions hotspots, it is a critical, but overlooked, point of intervention. Decarbonizing supply chain emissions is both an environmental necessity and a business imperative (Hettler and Graf-Vlachy, 2024). In many sectors, Scope 3 emissions account for over 75% of total emissions (Alvarez et al., 2014; Kjaer et al., 2015; Rossi, 2007). Supply chain emissions are, on average, 5.5 times higher than direct emissions (Bové and Swartz, 2016), with logistics alone contributing 8–9% of global GHG emissions (Suzanne Greene, 2023). Yet, most companies struggle to manage these emissions due to fragmented data and methodological inconsistencies (Forin et al., 2019; Stridsland et al., 2023a; Vieira et al., 2024).

Companies like Unilever demonstrate that integrating carbon metrics into procurement decisions, through supplier engagement, emissions disclosure, and low-carbon sourcing, can drive substantial reductions in Scope 3 emissions (Unilever, 2024).This approach supports both regulatory compliance and long-term competitiveness. Indeed, investors, regulators, and consumers increasingly expect companies to address emissions across their value chains, with failure to act resulting in financial, reputational, and regulatory risks (Zhong et al., 2021).

Nonetheless, it is a challenging goal. Complex, multi-tiered global supply chains hinder data reliability, especially in diverse regulatory contexts where emissions standards vary (de Camargo et al., 2019; Namdar et al., 2025). Additionally, traditional procurement practices often prioritize cost and efficiency over sustainability, with teams lacking tools, incentives, and expertise to assess carbon performance meaningfully (Cucchi et al., 2023; Matas et al., 2025). This challenge is compounded by the use of spend-based emissions estimates, which rely on aggregated emission factors and therefore obscure supplier-level differences in carbon performance (Georgiou et al., 2019).

To overcome these barriers, companies must adopt advanced emissions tracking methods, build supplier capacity, and integrate sustainability into procurement strategy (Busse et al., 2016; Diebel et al., 2024). Doing so not only supports compliance with emerging regulations but also enhances resilience, efficiency, and competitive positioning in the transition to a low-carbon economy (Mähönen et al., 2023).

This growing pressure on companies to decarbonize their supply chains is further reinforced by an evolving regulatory landscape, which is embedding climate accountability into procurement practices (Bernardini et al., 2025).

Global climate action is accelerating through stricter regulations that mandate corporate decarbonization, particularly across supply chains. The Paris Agreement (UN, 2015a) set a binding goal to limit global warming to well below 2°C, driving governments to enforce emissions reductions across industries. Complementing these policies, the Science-Based Targets initiative (SBTi, 2024b) requires companies with significant Scope 3 emissions to set targets: 67% coverage within 5–10 years for short-term goals and 90% by 2050 for long-term alignment with the 1.5°C target. Regulatory focus is now shifting from disclosure to mandatory emissions reductions, placing supply chain decarbonization and procurement at the center of corporate climate strategy.

The Corporate Sustainability Reporting Directive (CSRD) marks a major step forward in EU corporate sustainability disclosure by significantly expanding mandatory ESG reporting, from around 11,000 to 50,000 big companies (European Commission, 2023a). To ensure consistency and comparability, the European Financial Reporting Advisory Group (EFRAG) developed the European Sustainability Reporting Standards (ESRS), covering Environmental, Social, and Governance dimensions (UNEPFI, 2024). The environmental pillar of the ESRS includes five key areas: Climate Change (E1), Pollution (E2), Water and Marine Resources (E3), Biodiversity and Ecosystems (E4), and Resource Use and Circular Economy (E5).

Under ESRS E1 (Climate Change), the CSRD requires companies to report Scope 1, 2, and 3 emissions, with a strong emphasis on Scope 3 categories like “Purchased Goods and Services”, which often represent the largest portion of a company’s Scope 3 emissions (Figure 1-1). This highlights procurement's central role in decarbonization and compliance.

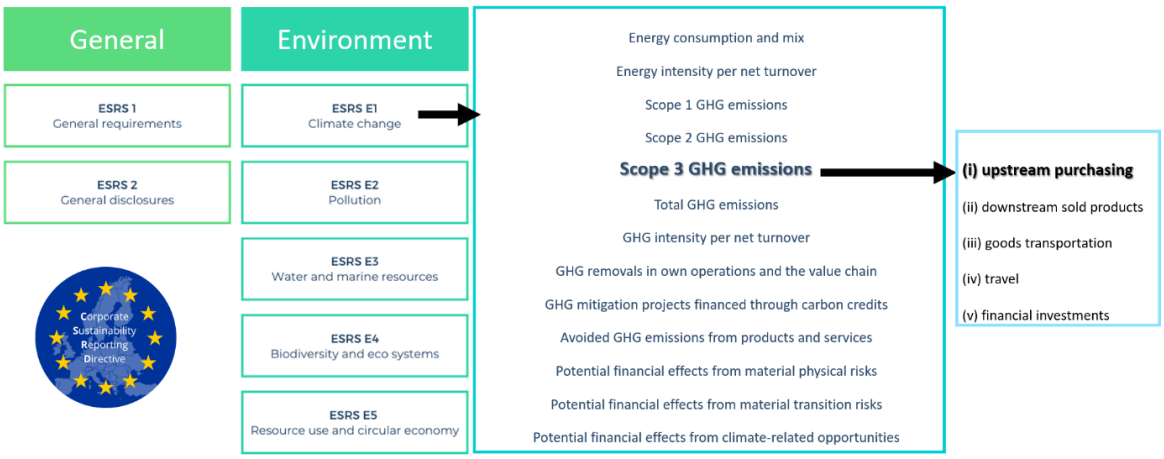


Figure 1-1 ESRS E1 and Scope 3 GHG Emissions: The Upstream Purchasing in Climate Reporting

CSRD also introduces the double materiality principle, obliging firms to assess both how sustainability risks affect financial performance (financial materiality) and how their operations impact the environment and society (impact materiality) (Dunfjäll, 2025). By mandating detailed, auditable disclosures, CSRD ensures that climate risk, emissions reduction, and supply chain sustainability are embedded in corporate strategies (Papafloratos and Pantazi, 2025). Ultimately, CSRD drives companies to integrate sustainability into procurement practices, reinforcing supplier engagement, emissions tracking, and alignment with long-term climate goals.

The EU Taxonomy for Sustainable Activities complements the CSRD by offering a classification system that defines what constitutes environmentally sustainable economic activities (European Commission, 2025a), guiding companies and investors in aligning investments and procurement with climate goals (Lucarelli et al., 2023). It enables evaluation of corporate activities based on criteria such as climate mitigation, adaptation, resource efficiency, and pollution prevention (Ostojic et al., 2024). However, the introduction of the EU Omnibus Simplification Package (2024) seeks to reduce the reporting burden within frameworks like the CSRD (European Commission, 2025b). While aimed at enhancing competitiveness, this move has raised concerns over potentially weakening transparency and accountability, particularly in the reporting of supplier emissions and corporate climate impacts (Jemal and Schmidt, 2025).

Beyond the European Union, climate-related regulations are rapidly expanding globally, reinforcing the need for companies to integrate sustainability into decision-making. In the United States, the Securities and Exchange Commission (2024) has proposed rules requiring Scope 3 emissions disclosure when material, enhancing transparency on supply chain impacts. California has taken a stricter stance with the Climate Corporate Data Accountability Act, mandating Scope 3 reporting for companies with over $1 billion in revenue (California Legislature, 2023). Similarly, Australia is advancing toward comprehensive mandatory emissions disclosure, including procurement-related emissions, positioning itself as a regulatory leader outside the (ASIC, 2024).

As businesses increasingly rely on sustainability disclosures to drive strategic decisions, many companies face challenges in collecting accurate and consistent sustainability data, particularly for Scope 3 emissions, which remain fragmented across supply chains. The integration of carbon accounting into financial reporting offers a structured solution, ensuring that emissions data is tracked with the same level of rigor as financial metrics. This shift strengthens corporate accountability, aligns procurement strategies with decarbonization objectives, and enhances compliance with emerging regulatory standards.

Accounting for Impact: Integrating ESG into Corporate Strategy

Traditionally centered on the recording and analysis of financial data, accounting has served as a foundational tool for tracking economic activities. Its origins trace back to Luca Pacioli's introduction of double-entry bookkeeping in 1494, which laid the groundwork for systematic financial tracking (Pacioli, 1494). Over time, the discipline evolved in response to changing corporate needs: the AICPA defined accounting in 1941 as the process of recording, classifying, summarizing, and interpreting financial data (AICPA, 1941); by 1966, the AAA emphasized its role in decision-making (AAA, 1966); and by 1970, the Accounting Principles Board reinforced its function as a means to quantify financial performance and support economic choices (AICPA, 1970).

However, as businesses face increasing pressure to address environmental and social concerns, the role of accounting has expanded beyond financial reporting to incorporate sustainability considerations (Mahmoudian et al., 2021). This shift has positioned accounting as a strategic instrument for integrating ESG factors, enabling companies to assess their overall impact more holistically (Kaplan and Ramanna, 2021).

Yet, despite this evolution, traditional financial accounting frameworks remain ill-equipped to capture the full scope of environmental and social impacts, revealing critical limitations in their ability to support sustainability-oriented decision-making.

Traditional financial accounting frameworks face major limitations in capturing environmental and social impacts, leading to an incomplete picture of corporate sustainability (Milne, 1996). They focus on monetary transactions and profitability, often neglecting non-financial metrics such as carbon emissions, biodiversity loss, and labor practices (Kaplan and Ramanna, 2021). This results in misaligned incentives and short-termism.

Most frameworks fail to internalize negative externalities like pollution, resource depletion, and climate risks, meaning environmental damages are rarely reflected in financial statements (Jones, 2003). Companies thus underprice natural resources and underestimate carbon-related liabilities. The historical nature of accounting further limits its usefulness for forward-looking sustainability strategies (Bebbington and Unerman, 2018).

Accounting also overlooks circular economy initiatives or environmental assets such as ecosystems or natural capital, as traditional models follow a linear view of production and fail to value resource efficiency (Varaniūtė et al., 2022). Inconsistent standards across industries further hamper comparability and transparency (Bebbington and Unerman, 2018).

Additionally, indirect sustainability costs like reputational damage or supply chain risk are not systematically captured, exposing companies to long-term performance risks (Berry and Rondinelli, 1998). Externalities borne by society, such as pollution impacts on health, remain unaccounted for, perpetuating unsustainable practices (Bergeron, 2010).

Given these limitations, a shift beyond traditional financial metrics is necessary to fully capture corporate sustainability performance and support long-term, ESG-aligned decision-making (Kaplan and Ramanna, 2021; Naro and Rambaud, 2023).

Addressing today's major sustainability challenges (climate change, biodiversity loss, and social inequality) requires companies to move beyond profit-centric models and embed sustainability throughout their operations and disclosures (Marinho Neto et al., 2018). To align with sustainability goals, accounting must now integrate environmental and social considerations alongside financial performance (Esteban-Amaro et al., 2024). As emphasized by Caby et al. (2013), corporate governance and value creation are increasingly influenced by sustainability imperatives, calling for a deeper integration of environmental and social concerns into corporate practices.

This evolution toward ESG-focused accounting reflects a broader shift in how companies manage value creation and corporate responsibility. ESG dimensions are increasingly embedded in corporate reporting, with notable progress in environmental accounting, particularly for climate-related impacts (Kaplan and Ramanna, 2021; Marinho Neto et al., 2018). Despite these advances, integrating environmental costs into traditional systems remains complex (Ayinla et al., 2024).

In response to this need, several new frameworks have been proposed to incorporate environmental and social dimensions into corporate decision-making (Trébucq, 2023). These models move beyond monetary performance, aiming to reflect the interconnected nature of economic, environmental, and social value creation.

The Universal Accounting Model (UAM) introduced a triple-accounting approach that quantifies financial, social, and environmental performance using monetary terms. While innovative, it struggled with practical implementation due to challenges in valuing non-financial impacts and a lack of institutional backing (Schoun et al., 2012).

Building on UAM, the CARE Model proposed by Rambaud and Richard (2015), emphasized the preservation of natural and human capital. It introduced the cost-of-maintenance principle, requiring companies to treat the conservation of ecosystems and workforce well-being as financial obligations. Despite its ethical grounding, the model faces difficulties in accurately valuing biodiversity and other sustainability assets.

The SeMA Model expanded the scope by placing social impacts on equal footing with environmental ones, using a parallel reporting structure to display sustainability metrics alongside financial data. While this dual-column approach improves transparency, the model still faces subjectivity and inconsistency in valuing social externalities (Bellini and Mathieu, 2017).

The more recent LIFTS Model offers a comprehensive, life-cycle-based perspective aligned with planetary boundaries and social foundations (Audencia, 2022). By accounting for upstream, operational, and downstream impacts, it supports more holistic sustainability performance tracking. However, data intensity and standardization challenges limit its accessibility, especially for smaller firms.

Beyond dedicated sustainability models, Activity-Based Costing (ABC) offers a practical method to connect financial and environmental accounting. Originally developed to allocate overhead costs by linking them to specific activities (Cooper and Kaplan, 1988), ABC has been adapted for environmental purposes, known as Environmental ABC, to trace impacts like carbon emissions and energy use back to their operational sources (Antić et al., 2021; Jourdaine et al., 2021; Yang et al., 2016). This level of detail is especially useful for managing Scope 3 emissions, which are often dispersed across fragmented supply chains.

By attributing emissions to specific activities, ABC improves emissions accuracy and helps identify key areas for intervention. A notable example is the hybrid model by Jourdaine et al. (2021), which combines ABC with Life Cycle Assessment (LCA) to map both emissions and costs to individual processes in the wine sector. This integration supports more informed and targeted sustainability decisions.

When used with LCA, ABC enables organizations to move beyond generic emission estimates and implement data-driven procurement strategies aligned with carbon goals and compliance requirements (Ortiz-Cea et al., 2025). This approach enhances transparency and accountability, helping companies build more sustainable and resilient supply chains.

While these models contribute conceptually to the evolution of sustainability accounting, standardized reporting frameworks have become essential for practical implementation and regulatory compliance.

To ensure transparency and regulatory compliance, a range of reporting frameworks has emerged to guide companies in disclosing their carbon emissions and broader ESG indicators. These frameworks enhance corporate accountability and provide stakeholders with reliable, standardized data for decision-making. By aligning corporate reporting with climate policy goals, they help reduce compliance risks and promote a more sustainable economy (Ibrahim et al., 2024).

Among the most influential frameworks are the Global Reporting Initiative (GRI, 2023), which offers broad ESG disclosure guidelines; the Sustainability Accounting Standards Board (SASB, 2025), which provides industry-specific standards for financially material ESG factors; and the Task Force on Climate-Related Financial Disclosures (TCFD, 2017), which integrates climate risk into corporate governance and strategy. The Carbon Disclosure Project (CDP, 2023), enables companies to benchmark their environmental performance through global disclosures, while the International Sustainability Standards Board (ISSB, 2023), aims to harmonize these frameworks into a unified global standard.

Together, these initiatives strengthen transparency, improve investor confidence, and equip companies to respond effectively to rising regulatory demands (Comoli et al., 2023). At the same time, they have elevated the role of accountants, whose expertise is now critical in navigating extra-financial disclosures and advancing corporate decarbonization (de Souza Barbosa et al., 2023).

The transformation of accounting into a sustainability-focused discipline marks a significant shift in corporate strategy and decision-making. Accountants now play a central role in managing ESG reporting, integrating sustainability metrics into financial systems, and ensuring compliance with evolving regulatory standards such as CSRD, SEC Climate Rules, and ISSB guidelines (Chen et al., 2019; Mahmoudian et al., 2021). Their responsibilities extend beyond financial recordkeeping to include strategic advisory functions, carbon accounting, and climate risk analysis (Naro and Rambaud, 2023).

Through tools like integrated reporting and E-ABC, accountants link environmental impacts to operational drivers, supporting more informed procurement and investment decisions (Antić et al., 2021; Jourdaine et al., 2021). They also help standardize and verify Scope 3 emissions data, ensuring supplier performance aligns with decarbonization goals (Ortiz-Cea et al., 2025). By incorporating climate risks into financial planning, including carbon pricing and supply chain vulnerabilities, accountants strengthen corporate resilience and investor confidence (Comoli et al., 2023).

Ultimately, their role enables businesses to align profitability with sustainability, positioning accounting as a key enabler of responsible corporate transformation (Trébucq, 2006). Yet, sustainable procurement must move beyond carbon alone to address broader environmental and social impacts, calling for a more holistic and inclusive approach.

Beyond Carbon: A Holistic Approach to Sustainable Procurement

While carbon emissions remain a central focus of corporate sustainability efforts, limiting sustainability considerations in procurement to carbon footprints alone is insufficient (Bernardini et al., 2025). Procurement decisions influence a wide range of environmental, social, and economic impacts beyond GHG emissions (Hinterhuber and Khan, 2025). As businesses transition toward responsible sourcing, it

is essential to adopt a more holistic approach to sustainability that encompasses biodiversity preservation, resource efficiency, ethical labor practices, and circular economy principles (Marinho Neto et al., 2018). Focusing corporate procurement solely on carbon emissions is increasingly seen as inadequate. While climate mitigation remains a key priority, a narrow carbon-centric view risks overlooking other critical dimensions of sustainability and may even lead to burden shifting, where efforts to reduce GHGs inadvertently cause harm in other areas such as biodiversity, labor conditions or supply risk (Clift and Druckman, 2016; Retamal et al., 2022).

From an environmental perspective, procurement influences a wide range of impacts not captured by carbon metrics alone, including land use, pollution, and natural resource depletion. Frameworks such as LCA and circular economy principles offer tools to avoid these trade-offs by promoting resource efficiency, product longevity, and end-of-life responsibility (Geissdoerfer et al., 2017; Sonnemann and Margni, 2015).

Beyond environmental performance, sustainable procurement must also address social risks, including labor rights, equity, and working conditions, through transparent supplier engagement and alignment with international standards (European Commission, 2019a; Seuring and Müller, 2008). In parallel, economic sustainability demands attention to supply chain resilience, diversification, and long-term value creation, especially in the face of regulatory change and geopolitical uncertainty (McMillan, 2025). A multidimensional approach that integrates environmental, social, and economic considerations is essential to ensure procurement contributes to global sustainability goals (SDGs) (UN, 2015b), without solving one problem by creating another. Operationalizing this holistic vision of sustainable procurement requires more than expanded goals, it demands robust methodologies, supplier collaboration, and digital infrastructure to track, reduce, and verify environmental and social impacts across complex supply chains.

Addressing the procurement-related emissions challenges requires a multi-faceted approach that combines supplier engagement, data transparency, regulatory alignment, and digital transformation (UNFCCC, 2024). Companies must move beyond compliance-driven approaches and proactively engage suppliers in decarbonization and sustainability programs, leveraging digital platforms and AI-driven sustainability assessments to enhance emissions tracking (Cho and Ackom, 2025). The adoption of resilient procurement strategies, including supplier diversification, low-carbon material sourcing, and localized production, can further mitigate risks associated with resource dependency and emissions leakage (Lintukangas et al., 2023). Ultimately, effective emissions tracking and supplier engagement are critical for achieving net-zero goals and ensuring corporate carbon-resilience in a rapidly evolving regulatory landscape.

A key component of sustainable procurement is supplier engagement programs, which encourage suppliers to disclose and reduce emissions through sustainability scorecards, training, and incentive mechanisms (SBTi, 2023). Several companies have demonstrated the effectiveness of supplier engagement in reducing procurement-related emissions. Walmart's Gigaton Project, for instance, aims to eliminate one billion metric tons (a gigaton) of GHG emissions from its supply chain by 2030. This initiative encourages suppliers to adopt sustainable practices through incentives, data-sharing, and technical support (Walmart, 2024). Similarly, Apple has committed to making its entire supply chain carbon-neutral by 2030, requiring all suppliers to use 100% renewable energy and track emissions reductions. These programs exemplify how supplier collaboration and incentives can accelerate Scope 3 decarbonization (Apple, 2022). These initiatives align with the ISO 20400 (2017) framework, which establishes principles for sustainable procurement and emphasizes life-cycle thinking, risk mitigation, and supplier collaboration.

To make procurement resilient and sustainable, companies are adopting advanced sustainability accounting methodologies, such as LCA, Environmentally Extended Input-Output (EEIO) analysis, and hybrid models, that integrate the granular accuracy of LCA with the systemic scope of EEIO, to enhance emissions tracking accuracy and inform purchasing decisions (Finogenova et al., 2019; Wiedmann et al., 2011; Yu and Wiedmann, 2018). Organizational Life Cycle Assessment (O-LCA) further strengthens this approach by allowing businesses to quantify the environmental impacts of procurement decisions across the entire supply chain, identifying high-emission suppliers, and integrating sustainability criteria into sourcing strategies (Cimprich et al., 2019). Unlike traditional LCA, which focuses on individual products, O-LCA assesses emissions at the organizational level, providing a more comprehensive understanding of corporate environmental impacts, particularly in multi-level supply chains (UNEP, 2015). By applying O-LCA, companies can evaluate supplier-specific emissions, improve procurement transparency, and ensure compliance with regulations such as CSRD, which require Scope 3 disclosures (de Salles and Brantsch, 2025) .

Building on these life cycle-based methodologies, the European Commission developed the Product Environmental Footprint (PEF) and Organization Environmental Footprint (OEF) frameworks to harmonize how environmental impacts are calculated and communicated across sectors in the EU. Both frameworks rely on LCA principles and provide science-based methods for quantifying environmental performance in a standardized and comparable manner. PEF focuses on assessing impacts at the product level, while OEF addresses environmental performance across organizational activities (Damiani et al., 2022). These methodologies are foundational to several key EU policy instruments, including the Green Claims Directive, which mandates the substantiation of environmental claims with robust data (European Commission, 2023b), and the upcoming Ecodesign

for Sustainable Products Regulation (ESPR), which will extend sustainability requirements across product life cycles (European Commission, 2024). Procurement professionals can use PEF and OEF to integrate standardized, verifiable sustainability data into supplier evaluation, ensuring that sourcing decisions align with environmental performance expectations and regulatory compliance.

In parallel to EU initiatives, the WBCSD launched the Partnership for Carbon Transparency (PACT) to address the global challenge of supplier-specific, interoperable carbon data exchange. PACT is a pre-competitive, industry-led initiative that enables the secure transmission of product-level emissions data across complex value chains, supporting transparent Scope 3 reporting and decarbonization. By fostering alignment between existing accounting standards, digital platforms, and sector initiatives, PACT creates an interoperable ecosystem where verified carbon data can be shared between partners in a consistent, machine-readable format (WBCSD, 2023a).

At the core of PACT is the Pathfinder Framework, a standardized methodology for calculating and exchanging Product Carbon Footprints (PCFs). Developed in collaboration with industry stakeholders, the framework defines consistent accounting rules and supports secure digital transmission of emissions data (WBCSD, 2023b). It aligns with globally recognized standards such as the GHG Protocol, ISO 14064, and the EU's PEF/OEF methodologies, and interfaces with key digital platforms such as Catena-X, which supports cross-industry data interoperability (Catena-X, 2024), and Together for Sustainability (TfS), which facilitates shared supplier assessments and sustainability performance data across global value chains (TFS, 2024). The Pathfinder Framework empowers companies to move beyond generic, spend-based estimates by embedding traceable, supplier-specific emissions data directly into procurement and sustainability accounting systems (WBCSD, 2023b).

These tools allow organizations to shift from high-level approximations to fact-based, interoperable carbon data, supporting more accurate supplier evaluations, improved climate disclosures, and alignment with legislative frameworks such. As procurement functions evolve from compliance-driven reporting toward proactive sustainability strategy, these developments equip companies with the tools to embed ESG performance into sourcing decisions, reduce supply chain emissions, and build long-term operational resilience.

II. Problem Statement and Research Question

Based on the overview provided in the previous section, procurement plays a crucial role in corporate decarbonization (Hettler and Graf-Vlachy, 2024) due to its influence over Scope 3 emissions, which are primarily linked to purchased goods and services (SBTi, 2024a; WRI and WBCSD, 2013). Despite increasing pressure from regulators and stakeholders to disclose and reduce these emissions (Baehr

et al., 2024), companies face persistent challenges in obtaining accurate data from their suppliers (Busse et al., 2016; Diebel et al., 2024; Jungbluth et al., 2016). In the absence of such data, they often default to using generalized industry-average emission factors, which compromise the reliability and comparability of emissions reporting across organizations and supply chains (Forin et al., 2019).

Existing accounting frameworks, such as the GHG Protocol, offer valuable guidance but lack harmonized methodologies tailored to the complexity of procurement emissions (Diebel et al., 2024). This methodological fragmentation results in inconsistencies that undermine transparency and strategic decision-making (Vieira et al., 2024). Furthermore, while financial accounting data is typically robust, auditable, and standardized, it is rarely integrated with environmental and social performance data, leaving a critical gap in sustainability assessments (Marinho Neto et al., 2018). Sustainability data, in contrast, remains decentralized, non-standardized, and often unaudited, limiting its utility in formal procurement and accounting processes (Loreti et al., 2001). The growing volume and complexity of sustainability data further complicate reporting and innovation, highlighting the need for automation to support accountants and procurement professionals in processing large datasets and improving data reliability (Varaniūtė et al., 2022).

To address these challenges, procurement must evolve beyond a carbon- or compliance-driven approach (Valdivia and Sonnemann, 2024). It requires tools and models that enable companies to integrate environmental and social considerations alongside financial metrics in procurement decisions (Seuring and Müller, 2008). However, many current procurement strategies remain narrowly focused on cost efficiency and short-term performance, lacking the data infrastructure and analytical frameworks needed to balance climate goals with long-term economic and social resilience (Trébucq, 2023). Bridging this gap is essential for transforming procurement into a strategic driver of corporate sustainability and achieving meaningful Scope 3 emissions reductions.

This research seeks to answer the following central question:

How can businesses integrate accurate procurement-line level data - encompassing both environmental and social dimensions - into existing financial accounting frameworks to support corporate decarbonization, move beyond carbon-centric approaches, and enable holistic, data-driven sustainability decision-making?

Accurate data refers to data that is reliable, up-to-date, granular, preferably supplier-specific, and representative of real-world conditions, enabling credible and fact-based decision-making in procurement and sustainability accounting.

This research aims to develop a data-driven, integrated procurement and accounting model that ensures accurate sustainability reporting, supplier accountability, and strategic decision-making for long-term corporate resilience and innovation. The approach is designed to support transparent reporting regardless of the type of available data, while enabling innovative, performance-based procurement strategies when supplier-specific data is accessible.

III. Research Interest

This research is grounded in the need to operationalize hybrid accounting approaches that bridge financial, environmental, and social dimensions in procurement decision-making (Comoli et al., 2023; Hinterhuber and Khan, 2025; Varaniūtė et al., 2022). While regulatory frameworks have advanced in mandating emissions disclosure (Baehr et al., 2024), many companies still lack methodological clarity and operational tools to translate heterogeneous supplier data, whether monetary, physical, or line-level, into actionable sustainability metrics (Aigner, 2024; Vieira et al., 2024). Especially in large procurement portfolios, the reliance on generalized, spend-based data remains common, not due to ignorance of its limitations, but due to technical and organizational constraints in accessing and using more granular supplier-specific data (SBTi, 2024a).

Despite growing interest in supplier engagement and value chain sustainability, no academic studies have mobilized supplier-level emissions data at the procurement-line level, which represents a critical gap in existing research. Most studies continue to rely on proxy data, either economic or physical, rather than capturing traceable emissions data directly linked to procurement actions (Cimprich et al., 2019; Finogenova et al., 2019; Keil, 2023; Paepe et al., 2023; Suh, 2009). This thesis addresses that gap by designing and testing a framework that can work flexibly across different levels of data availability: from generalized impact factors to supplier-specific data at the procurement-line level. It aims to support both credible reporting and performance-driven innovation.

The University of Bordeaux has become a key ecosystem for such interdisciplinary experimentation. Drawing on expertise from IRGO in social and financial accounting, and from CyVi (ISM) in Life Cycle Sustainability Assessment, this research continues an institutional trajectory that seeks to embed environmental and social performance into corporate systems. It builds on the precedent set by the doctoral work of Jourdaine (2020) which integrated ABC with LCA. However, a new frontier explored in this thesis is the inclusion of the social dimension, a critical yet underdeveloped component in existing hybrid models. This ambition is supported by ongoing questions at IRGO around how to meaningfully integrate social criteria, such as labor conditions, equity, and supply chain vulnerabilities, into accounting systems traditionally focused on environmental and financial metrics. By designing a

framework that accounts for upstream impacts, the thesis contributes to the methodological development of sustainability accounting beyond carbon.

A key turning point in the research was the establishment of a collaboration with Eiffage, one of Europe's leading construction and infrastructure companies. It began at the LCM 2023 conference in Lille, where early thesis results were shared via a poster on linking monetary procurement data with environmental indicators, particularly Scope 3 emissions, through a hybrid accounting model (Essouid et al., 2023).

The proposal resonated with representatives from Eiffage's procurement department, who were actively exploring alternatives to improve the quality of their Scope 3 emission methodology. Initial interest from procurement staff led to further exchanges, including an in-person visit to the University of Bordeaux, where the research directions were discussed in detail.

These interactions revealed a shared recognition of the limitations of spend-based methodologies and the urgent need for scalable, more accurate tools to support impact-driven decision-making and effective decarbonization planning. In particular, Eiffage expressed interest in improving the granularity of emissions accounting by moving beyond proxies and incorporating supplier-specific data at the procurement-line level, a precision level not addressed in current models.

By July 2024, the collaboration was formalized through the signing of a Non-Disclosure Agreement (NDA), enabling structured data exchange and the development of a real-world case study. Eiffage was chosen not only for its operational complexity, spanning large, multi-tiered procurement systems, but also for its strategic commitment to sustainability and digital innovation. The company aimed to test the model under real procurement constraints using both generalized emission factors and, where possible, supplier-specific data. Since then, Eiffage has become the primary pilot site for testing the thesis model. The partnership offers a unique opportunity to evaluate its scalability, flexibility, and decision-making value across different supplier contexts and regulatory settings, while contributing directly to Eiffage's climate goals.

The applied nature of the research justifies the use of a case study approach to explore real-world implementation and impact. As Yin (2014) argues, case studies are particularly effective when the research addresses "how" and "why" questions. Stake (1995) and Eisenhardt (1989) reinforce this view, highlighting the method's capacity to capture dynamic, real-world processes. In this research, where the integration of sustainability dimensions into procurement decisions is tightly interwoven with organizational realities, Eiffage case study offers a rigorous and appropriate setting for evaluating both feasibility and managerial impact.

IV. Thesis Objectives and Structure

This thesis explores how procurement-line level data can be integrated into corporate sustainability accounting to support decarbonization and impact-driven decision-making. Structured around four thematic objectives and corresponding research questions, it addresses the current lack of models that operationalize environmental and social data within accounting systems.

Figure 1-2 outlines the research structure, showing how the work progresses from understanding Scope 3 emissions to developing and evaluating a hybrid model that includes environmental and social dimensions. Each chapter contributes theoretical and empirical insights, ensuring a coherent path from literature review to practical application. The thesis is structured into six chapters, each with a specific thematic and methodological focus:

Chapter 1: General Introduction

The introductory chapter establishes the context, motivation, and overarching objectives of the research. It discusses the pressing need for more reliable and socially integrated sustainability accounting methods, particularly in the area of Scope 3 procurement-related emissions. The chapter introduces the conceptual foundations of the study, formulates the central research problem, and outlines the research questions and methodological strategy. It also provides an overview of the thesis structure and contributions.

Chapter 2: State of the Art and Methodological Review

This chapter presents a comprehensive review of existing approaches to Scope 3 accounting in the context of procurement, including corporate practices, tools, and reporting standards. It critically examines the extent to which current models integrate environmental and social dimensions alongside financial metrics. Through a comparative analysis of methodologies, it identifies gaps in practice and theory, particularly concerning the operationalization of social indicators and the connection between procurement-level data and accounting systems.

Objective 1: To understand the state of the art in Scope 3 emissions accounting, with a focus on procurement-related practices and the integration of environmental and social impact data into corporate accounting systems. This includes reviewing current methods, tools, and reporting practices used to assess sustainability performance across supply chains.

➔ **RQ 1:** What methods and practices are currently used to account for Scope 3 procurement-related impacts, and how effectively do they integrate environmental and social data with financial accounting to support corporate sustainability goals?

Chapter 3: Strategic Roadmapping for Scope 3 Procurement Emissions: Insights from MICMAC and the Sustainability Balanced Scorecard

This chapter addresses the systemic limitations that hinder the robustness and credibility of Scope 3 accounting practices. Drawing on systems thinking and interviews, it identifies technical, organizational, and methodological challenges that reduce data reliability. The analysis culminates in a strategic roadmap that proposes actionable improvements to enhance reliability and alignment between procurement practices and sustainability accounting frameworks.

Objective 2: To identify the key challenges affecting the reliability of Scope 3 procurement-related accounting, analyze their interdependencies, and develop a strategic roadmap to improve accounting practices for greater accuracy and sustainability integration.

➔ **RQ 2:** What are the key challenges affecting the reliability of Scope 3 procurement-related accounting, how are these challenges interdependent, and how can a strategic roadmap be developed to enhance accounting practices?

Chapter 4: Hybrid Environmental Accounting for Procurement: Methodology and Industrial Applications

This chapter introduces an innovative hybrid model designed to bridge the gap between high-level estimation techniques and granular procurement-level data. The model combines top-down input-output analysis with bottom-up data from suppliers and internal procurement records. It is applied and validated using real-world case studies in the construction sector, assessing its effectiveness in improving Scope 3 emission reporting and supporting practical sustainability decision-making.

Objective 3.1: To develop a hybrid model that systematically integrates bottom-up and top-down approaches with supplier-specific, procurement and financial accounting data to address data gaps and enhance the accuracy of Scope 3 carbon and broader environmental impact accounting.

➔ **RQ 3.1:** How can a hybrid model systematically integrate bottom-up and top-down supplier-specific, procurement and financial accounting data to address data gaps and improve the accuracy of Scope 3 carbon and broader environmental impact accounting?

Objective 3.2: To apply and evaluate the proposed hybrid model in an industrial context to assess its relevance, feasibility, and effectiveness for improving Scope 3 environmental impact accounting, and to explore its potential for supporting sustainability reporting, procurement decision-making, and sustainable innovation.

➔ **RQ 3.2:** How can the proposed hybrid model be applied and validated in an industrial context to assess its effectiveness in improving the accuracy and reliability of Scope 3 environmental impact

accounting, while also supporting corporate sustainability efforts such as reporting, procurement decision-making, and sustainable innovation?

Chapter 5: Advancing Social Integration in Procurement Sustainability Accounting

Building upon the hybrid model developed in Chapter 4, this chapter extends its scope to social dimensions of sustainability. It explores how social indicators can be meaningfully quantified and embedded into procurement and cost accounting processes. This chapter evaluates the feasibility and managerial implications of incorporating social criteria into supply chain decisions and enterprise systems.

Objective 4.1: To extend the top-down procurement accounting model by integrating social impact indicators, enabling a more holistic assessment and reporting of supply chain sustainability beyond carbon emissions.

➔ **RQ 4.1:** How can social impact indicators be effectively integrated into top-down procurement accounting models to improve the assessment of supply chain sustainability beyond carbon?

Objective 4.2: To explore how social impact indicators can be integrated into cost accounting systems, and evaluate the managerial relevance of this integration for procurement, supplier selection, and responsible sourcing.

➔ **RQ 4.2:** How can social impact indicators be embedded into cost accounting systems, and what managerial value does this integration provide for procurement-related decision-making and responsible sourcing strategies?

Chapter 6: Conclusions and Perspectives

The concluding chapter synthesizes the key findings from the entire thesis, offering a critical reflection on their theoretical, methodological, and practical implications. It discusses the main limitations and constraints encountered throughout the research process. Finally, it identifies promising directions for future research, particularly in enhancing the operational integration of environmental and social data into real-time decision-making and enterprise systems.

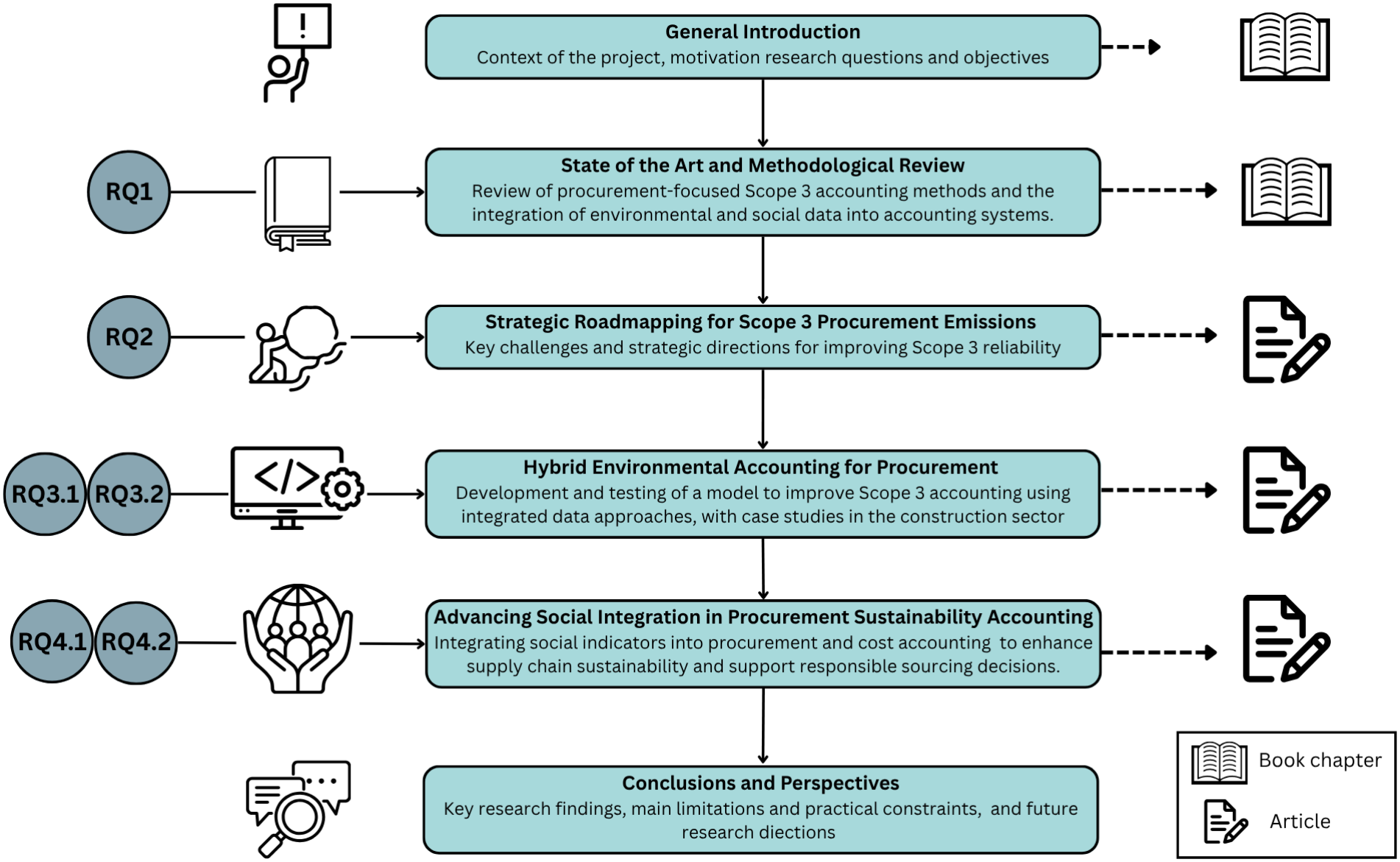

General Introduction
Context of the project, motivation research questions and objectives
RQ1
State of the Art and Methodological Review
Review of procurement-focused Scope 3 accounting methods and the integration of environmental and social data into accounting systems.
RQ2
Strategic Roadmapping for Scope 3 Procurement Emissions
Key challenges and strategic directions for improving Scope 3 reliability
RQ3.1
RQ3.2
Hybrid Environmental Accounting for Procurement
Development and testing of a model to improve Scope 3 accounting using integrated data approaches, with case studies in the construction sector
RQ4.1
RQ4.2
Advancing Social Integration in Procurement Sustainability Accounting
Integrating social indicators into procurement and cost accounting to enhance supply chain sustainability and support responsible sourcing decisions.
Conclusions and Perspectives
Key research findings, main limitations and practical constraints, and future research diections
Book chapter
Article

Figure 1-2 Thesis Structure

2| State of the Art and Methodological Review

This chapter explores the concepts and methods used to assess Scope 3 emissions from organizational procurement, focusing on both theoretical frameworks and practical applications. It is structured around two main sections:

(A) Theoretical Foundations and Methods for Environmental and Social Accounting in Sustainable Procurement, *which examines core accounting principles, sustainability metrics, and the integration of environmental and social data into procurement processes and enterprise systems; and*

(B) Review of Scope 3 Accounting Practices in Academic Literature, *which critically analyzes existing research on carbon and environmental impact accounting, with particular emphasis on procurement-level methodologies, advancements, and implementation challenges.*

Importantly, the chapter goes beyond carbon to address broader environmental and social dimensions of sustainability. By examining key methodologies and empirical case examples, it establishes a conceptual and methodological foundation for aligning procurement practices with strategic decision-making, regulatory compliance, innovation, and value chain-wide impact reduction.

A. Theoretical Foundations and Methods for Environmental and Social Accounting in Sustainable Procurement

This section provides a structured overview of sustainability accounting methods, ranging from conventional GHG accounting frameworks to advanced hybrid life cycle models, with a particular focus on how these approaches can inform sustainable procurement and organizational decision-making. A key focus of the section is the alignment of life cycle frameworks with enterprise systems and cost accounting structures, thereby enabling consistent tracking, performance evaluation, and prioritization of sustainability risks and opportunities. Beginning with carbon accounting via the GHG Protocol, the section expands toward different methods used in sustainability assessments and explores how costing approaches can digitally embed sustainability into enterprise systems.

I. The GHG Protocol: Scope-Based Classification of GHG Emissions

To manage and reduce GHG emissions, businesses commonly rely on the GHG Protocol, the most widely used framework for classifying, quantifying, and reporting emissions across operations and supply chains (WRI and WBCSD, 2011a).

The classification of GHG emissions into scopes was first introduced in September 2001 with the publication of the "Corporate Accounting and Reporting Standard for Greenhouse Gases". This standard remains the global reference for GHG emissions accounting, offering a comprehensive framework and a foundation for businesses to measure, track, report and manage their carbon footprint (WRI and WBCSD, 2011a). However, accounting alone does not reduce emissions (SBTi, 2024a). The GHG Protocol classifies emissions into three scopes, as seen in Figure 2-1, distinguishing between direct and indirect sources of emissions.

Scopes 1 essentially encompasses direct emissions that a company owns or directly controls, such as emissions from company-owned office buildings, factories, or vehicles.

Scope 2 includes indirect emissions associated with the consumption of purchased electricity, steam, heating, and cooling by the company. These emissions occur at the power plants or facilities that generate energy but are attributed to the company using it. For example, the emissions from power plants generating electricity used to charge an electric vehicle fleet fall into this category.

Scope 3 encompasses all other indirect emissions that occur throughout a company's value chain, beyond its direct operations and purchased energy. It is the most expansive and complex category, often accounting for the majority of a company's total GHG footprint. To enhance consistency and transparency in reporting, the GHG Protocol subdivides Scope 3 emissions into fifteen distinct categories, which are further grouped into upstream and downstream activities (Table 2-1).

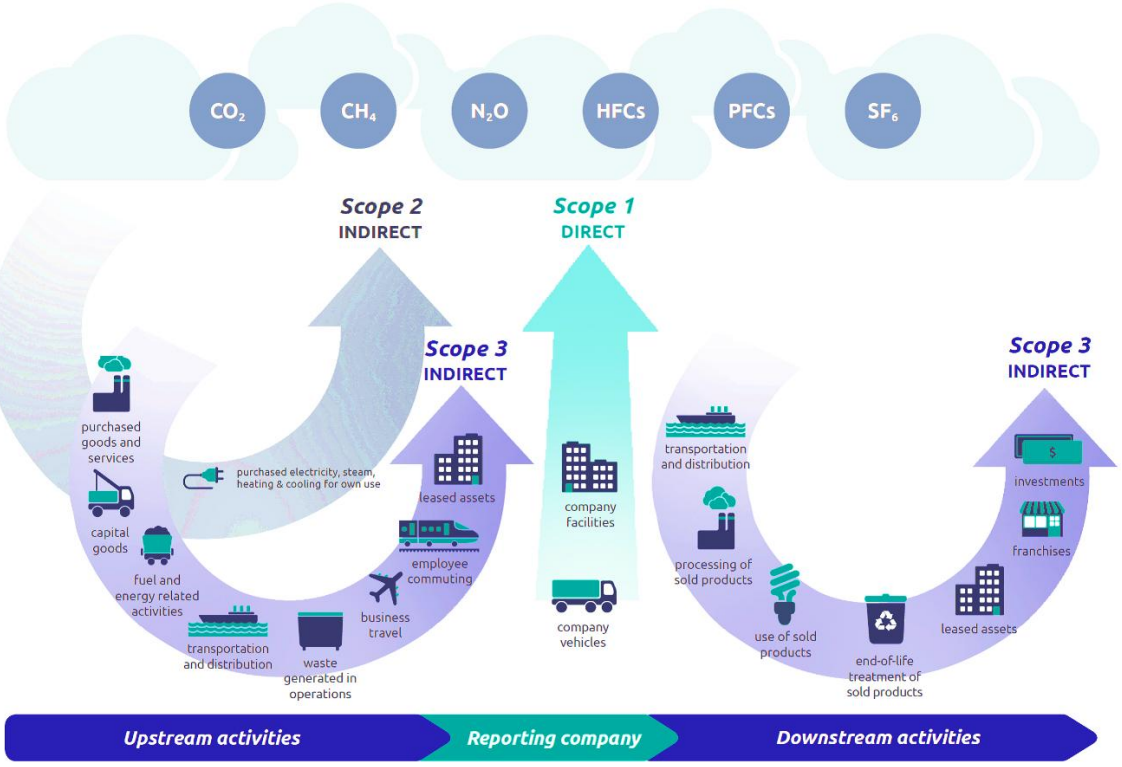


Figure 2-1 GHG Protocol, Scopes 1, 2, and 3 Emissions (WRI and WBCSD, 2011a)

These subcategories enable organizations to structure Scope 3 assessments according to their business models, supply chains, and customer relationships. In sectors such as construction, purchased goods and services, particularly materials like concrete, typically dominates the Scope 3 inventory, as will be explored in the following sections of this dissertation.

Table 2-1 Scope 3 Emission Categories Defined by the GHG Protocol

	Category	Description
Upstream Scope 3 categories	Purchased goods and services	emissions from the production of goods and services acquired by the company (e.g., construction materials, office supplies).
	Capital goods	emissions from the production of long-lived assets such as machinery, vehicles, or buildings.
	Fuel- and energy-related activities	emissions from extraction, production, and transport of fuels and energy purchased.
	Upstream transportation and distribution	emissions from third-party transport and logistics before the product reaches the company.
	Waste generated in operations	emissions from third-party treatment and disposal of operational waste.
	Business travel	emissions from travel by air, rail, car, or accommodation paid for by the company.
	Employee commuting	emissions from employee transport between home and the workplace.
	Upstream leased assets	emissions from assets leased by the company (if not included in Scope 1 or 2).

	Category	Description
Downstream Scope 3 categories	Downstream transportation and distribution	emissions from the transport and distribution of products sold.
	Processing of sold products	emissions resulting from the processing of intermediate products by third parties.
	Use of sold products	emissions generated by the end-users during the product's functional use.
	End-of-life treatment of sold products	emissions from disposal, recycling, or landfilling of products.
	Downstream leased assets	emissions from leased-out assets not included in Scope 1 or 2.
	Franchises	emissions from franchise operations not included in Scope 1 or 2.
	Investments	emissions from equity and debt investments.

While the GHG Protocol is primarily known for its Corporate Standard, which guides organizations in accounting for and reporting GHG emissions across Scopes 1, 2, and 3, it also includes a Product Standard (WRI and WBCSD, 2011b). This product-level framework allows companies to assess emissions associated with individual products across their full life cycle, from raw material extraction to end-of-life. Together, these standards enable consistent emissions tracking at both the organizational and product levels, supporting internal decision-making as well as external reporting and value chain engagement.

II. Life Cycle Sustainability Assessment (LCSA)

While the GHG Protocol provides a foundational framework for tracking and reporting greenhouse gas emissions, at both the organizational level through its Corporate Standard and the product level via its Product Life Cycle Standard, it remains primarily focused on carbon-related performance. This focus on carbon, while essential for climate mitigation, provides only a narrow view of sustainability, overlooking other critical environmental, social, and economic impacts linked to business activities (Hahn and Kühnen, 2013). As organizations are increasingly expected to align with Environmental, Social, and Governance (ESG) criteria and adopt Triple Bottom Line thinking, balancing environmental integrity, social equity, and economic viability, there is a growing need for a more comprehensive assessment tool (Byrne, 2024; Slaper and Hall, 2011).

Life Cycle Sustainability Assessment (LCSA) responds to this need by integrating three complementary methodologies: Life Cycle Assessment (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (S-LCA). These tools allow for a holistic evaluation of sustainability impacts throughout the life cycle of a product, service, or system (Finkbeiner et al., 2010; UNEP, 2011; Valdivia and Sonnemann, 2024).

LCSA is primarily applied at the product level, making it particularly relevant for comparing design alternatives, informing procurement choices, or improving product sustainability. However, it is increasingly being adapted for organizational-level applications, particularly in sectors with complex

value chains or high Scope 3 emissions (Omran et al., 2021; Wafa et al., 2022). When scaled appropriately, LCSA can support corporate strategy, sustainable sourcing policies, and stakeholder reporting.

- **LCA (Life Cycle Assessment)** quantifies environmental impacts such as GHG emissions, energy use, water consumption, and resource depletion. It supports hotspot identification across supply chains (ISO 14040, 2006; ISO 14044, 2006).
- **LCC (Life Cycle Costing)** evaluates the full economic cost of a product or system over its life cycle, including acquisition, operation, maintenance, and end-of-life phases. It enables financially informed sustainability decisions (Rödger et al., 2018; SETAC, 2011).
- **S-LCA (Social Life Cycle Assessment)** examines social impacts, including labor rights, community effects, health and safety, and fair working conditions, providing insights into areas often overlooked by environmental-focused assessments (ISO 14075, 2024; UNEP, 2020).

In high-impact sectors such as construction and manufacturing, where purchased goods and services account for a significant share of Scope 3 emissions (EEA, 2021), LCSA provides a structured way to assess the broader sustainability implications of upstream activities.

By complementing GHG accounting with multi-dimensional analysis, LCSA allows organizations to move beyond emissions tracking toward integrated sustainability performance management (Valdivia et al., 2021). It supports alignment with global frameworks such as the UN Sustainable Development Goals (SDGs), the EU Corporate Sustainability Reporting Directive (CSRD), and emerging ESG disclosure requirements (Finkbeiner et al., 2010).

III. Life Cycle Assessment (LCA)

Life Cycle Assessment (LCA) is a comprehensive methodology used to evaluate the potential environmental impacts (i.e., resource consumption and environmental emissions) associated with a product, process, or service across different phases of its entire life cycle (ISO 14040, 2006). These phases typically include raw material extraction, manufacturing, distribution, use, and end-of-life management. The process is often visualized in a circular representation, emphasizing the continuous flow of materials and potential for recycling or waste disposal.

Figure 2-2 illustrates the key stages of a product's life cycle, beginning with Raw Material Extraction, where natural resources are sourced, followed by Manufacturing, in which raw materials are transformed into finished or semi-finished products. The Distribution phase involves the movement of goods to retailers or consumers. During the Use phase, products are utilized, often consuming energy and requiring maintenance. Finally, the End-of-Life & Waste Management phase determines whether

a product is disposed of, recycled, or repurposed. The dashed arrows in the figure indicate different pathways for end-of-life treatment, such as landfill disposal or material recovery through recycling.

Depending on the study's scope, an LCA can follow different system boundaries, such as *cradle-to-gate*, which assesses impacts from raw material extraction to the factory gate (excluding use and disposal), or *cradle-to-grave*, which covers the entire life cycle from raw material extraction to end-of-life treatment. In some cases, *cradle-to-cradle* assessments focus on circularity by incorporating material recovery and recycling. By providing a holistic perspective on environmental performance, LCA has become a fundamental tool in sustainable decision-making, eco-design, regulatory compliance, and corporate environmental strategies, particularly at the product level**.**

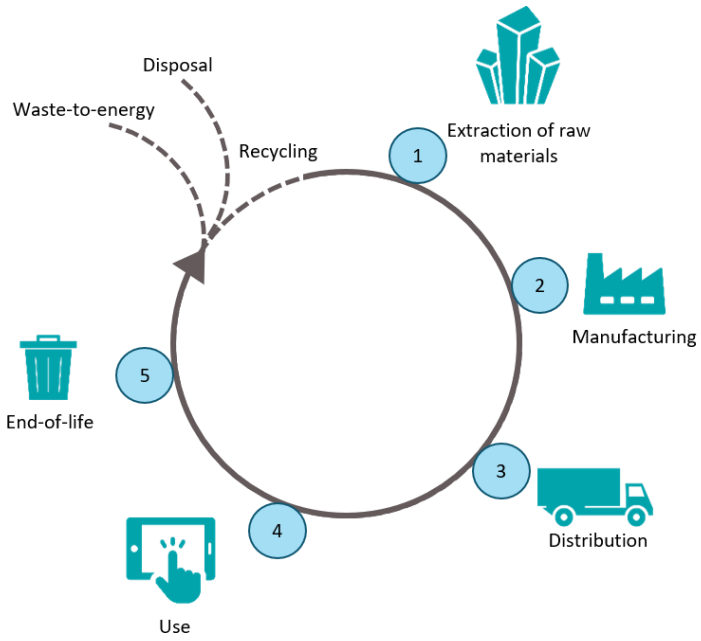


Figure 2-2 Key Stages of a Product's Life Cycle

III.1 Historical development of LCA

The conceptual foundations of LCA can be traced back to the 1960s when researchers conducted energy and material flow analyses to assess the environmental impact of different packaging materials, particularly beverage containers (Bjørn et al., 2018). These early studies aimed to identify resource consumption patterns and waste generation, laying the groundwork for what would later become a standardized methodology.

In the 1970s and 1980s, companies and governmental organizations increasingly adopted environmental accounting techniques, leading to the first structured life cycle inventories (LCI). The late 1980s marked a shift toward integrating impact assessment methodologies, and by the 1990s, the term Life Cycle Assessment gained widespread recognition (Guinée et al., 2011). The first commercial

LCA software tools were released during this period (Bjørn et al., 2018), allowing practitioners to conduct detailed environmental assessments more efficiently.

A significant milestone in LCA's formalization was the 1993 workshop in Sesimbra, Portugal, which resulted in the SETAC "Guidelines for Life-Cycle Assessment: A Code of Practice". These guidelines played a pivotal role in standardizing the methodology, particularly by framing interpretation as a phase that includes improvement analysis, thus emphasizing LCA's role in driving environmental enhancements (SETAC, 1993). This foundational work laid the path for the publication of the ISO 14040 (ISO 14040, 2006) series by the International Organization for Standardization (ISO) in the late 1990s and early 2000s. The standards, ISO 14040, ISO 14041, ISO 14042, and ISO 14043, established a structured framework for conducting LCAs, ensuring consistency, transparency, and comparability across studies. These standards were later consolidated and updated in ISO 14044 (ISO 14044, 2006), which remains the primary reference for LCA practitioners today.

III.2 Key principles of LCA

LCA is built upon several core principles that ensure its effectiveness and reliability in environmental decision-making:

- **Functional Unit**: The assessment is based on a well-defined functional unit, ensuring that comparisons between different products or systems are meaningful, (e.g., "one ton of product").
- **System Boundaries**: The scope of the assessment is carefully defined, specifying which processes, geographical regions, and timeframes are included, (e.g., cradle-to-gate or cradle-to-grave).
- **Holistic Perspective**: LCA evaluates environmental impacts across the entire life cycle, avoiding burden-shifting from one stage to another.
- **Data Quality and Transparency**: The reliability of an LCA depends on accurate and representative data, requiring clear documentation of sources and assumptions.
- **Iterative Process**: LCA is inherently iterative, meaning that insights from later stages may lead to refinement in earlier phases, improving overall accuracy.

III.3 Steps of LCA (ISO 14040 Framework)

LCA follows a structured four-step approach as defined by ISO 14040 and ISO 14044 (ISO 14040, 2006; ISO 14044, 2006):

Goal and Scope Definition

This step serves as the foundation for the entire assessment by clearly defining its purpose and methodological framework. The goal of the study establishes the intended application, the reasons for conducting the assessment, and the target audience. Meanwhile, the scope delineates essential

parameters such as the function of the system, the functional unit, and a detailed description of the system under study. It also defines the system boundaries, allocation procedures, impact categories, and the impact assessment model to be used. Furthermore, this step specifies data requirements, key assumptions, study limitations, and data quality criteria. If necessary, it also addresses peer review requirements, and the type of reporting expected. By structuring these elements, the goal and scope step ensures clarity and consistency, laying the groundwork for robust and reliable LCA results (Curran, 2016; Rebitzer et al., 2004).

Life Cycle Inventory (LCI)

This step is often the most time-consuming, requiring extensive data collection. In LCI Analysis, data collection is divided into *foreground* and *background* systems, each playing a crucial role in accurately modeling environmental impacts (Figure 2-3). The foreground system consists of processes directly related to the study, modeled using primary data collected from specific activities (also called activity data), manufacturers, or case studies. This includes direct inputs (e.g., raw materials, energy, water consumption, and intermediate products), on-site emissions (to air, water, and soil), waste generation, and co-products recorded through company reports or direct measurements. In contrast, the background system refers to processes that support the foreground system but are modeled using secondary data from commercial databases, literature or free datasets. These background processes include upstream and downstream activities like energy production, material extraction, and transportation, relying on industry averages rather than site-specific measurements. While primary data in the foreground system improves accuracy, secondary data from background databases fills critical gaps where direct measurement is impractical (Islam et al., 2016; Kalverkamp et al., 2020).

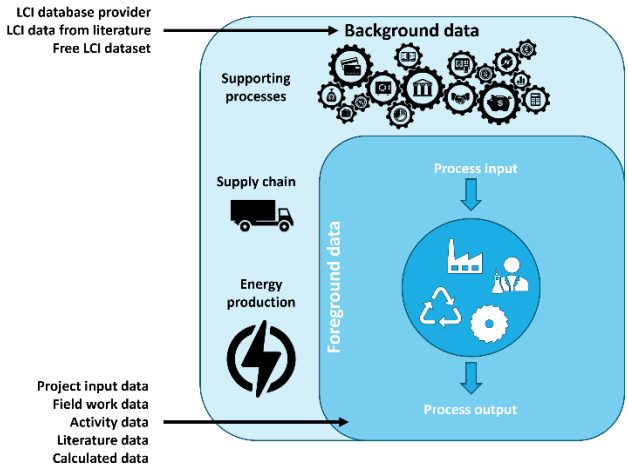


Figure 2-3 Distinction Between Foreground and Background Data in LCA

Inventory data can be collected using a bottom-up, top-down, or hybrid approach. Bottom-up methods, often used in product-level LCA, rely on detailed process-level data. Top-down methods,

such as those used in EEIO analysis, are based on macroeconomic data and sectoral emission factors. Hybrid inventory approaches combine both strategies to enhance system completeness and data robustness. In the context of Organizational LCA (O-LCA) and procurement emissions accounting, hybridization may also involve combining physical and monetary data, as well as supplier-specific and generic datasets, to better capture indirect impacts. These approaches and their methodological implications are discussed in detail in Section 2.B.III.2.

Life Cycle Impact Assessment (LCIA)

This step translates inventory data into environmental impact indicators, allowing for a structured evaluation of potential environmental burdens. This step involves a classification step to assign inventory flows to specific impact categories, such as greenhouse gas emissions contributing to climate change. Characterization then applies scientific models to quantify these flows into impact scores, such as CO_2 equivalents for global warming potential. Additionally, normalization and weighting (optional) express impacts relative to a reference system and prioritize them based on significance (UNEP, 2023). LCIA results can be assessed at two levels: midpoint and endpoint (Figure 2-4).

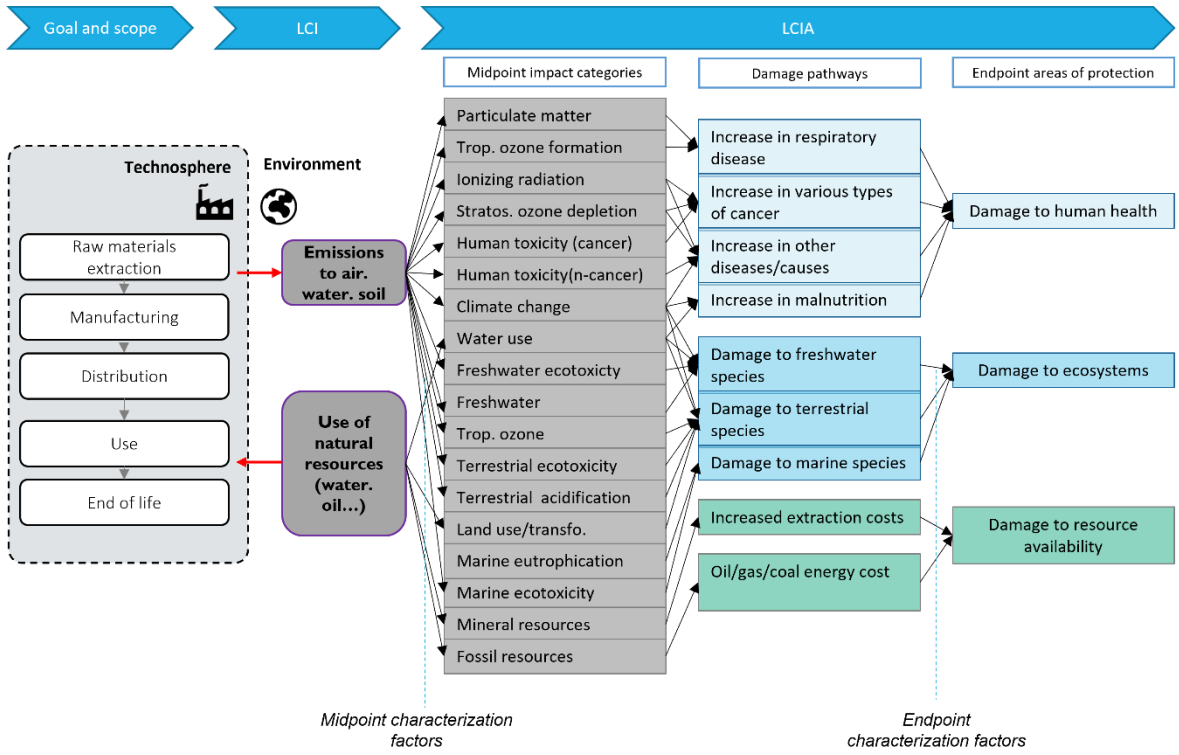


Figure 2-4 The Main Environmental Impact Categories in LCA Adapted from ReCiPe 2016 (Loubet, 2023)

Midpoint indicators focus on individual environmental problems, such as Global Warming Potential (GWP), Acidification Potential (AP), Eutrophication Potential (EP), and human toxicity and ecotoxicity. In contrast, endpoint indicators aggregate impacts into broader areas of protection, such as damage to human health, and ecosystem quality. Different LCIA methodologies, such as ReCiPe (Huijbregts et

al., 2016), EF (European Commission, 2021), and TRACI (US EPA, 2015), provide structured frameworks for assessing these impacts, ensuring consistency and comparability in environmental evaluations.

Interpretation

This is the final step in Life Cycle Assessment (LCA), where results are analyzed to derive meaningful conclusions and support decision-making. A key aspect of this stage is identifying hotspots, which are the most environmentally impactful stages of the life cycle. Additionally, comparing scenarios, such as evaluating alternative materials or processes, helps in assessing potential improvements. Another crucial step is assessing uncertainties and limitations to ensure the robustness of the findings. To enhance confidence in the results, this stage often incorporates sensitivity analyses, Monte Carlo simulations, or uncertainty assessments, providing a more reliable basis for environmental decision-making (Laurent et al., 2020).

LCA is an iterative process, meaning that insights from later steps may refine earlier steps, improving accuracy and relevance (Figure 2-5).

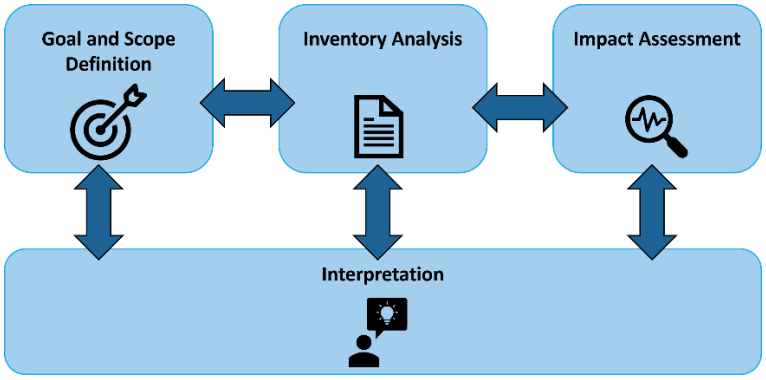


Figure 2-5 The Four Steps of LCA According to the ISO 14040 Standard

III.4 Computational framework of LCA

The computational framework of Life Cycle Assessment (LCA) provides a systematic approach to quantify environmental impacts by modeling the relationships between economic activities and their environmental burdens. The fundamental equation of LCA, as expressed in Equation 2-1, is given by:

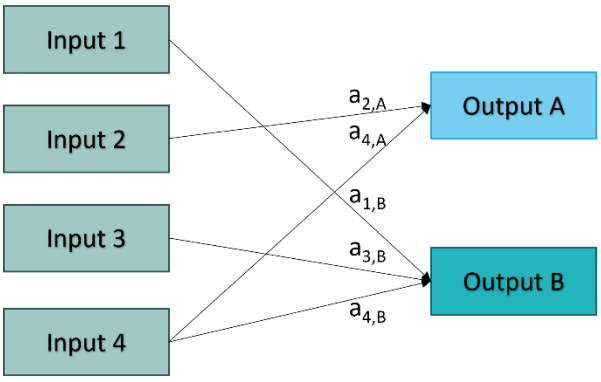
$$e_{LCA} = B_{LCA} \times C_{LCA} \times A_{LCA}^{-1}$$

Equation 2-1 Computational Equation of LCA

where e_{LCA} represents the environmental impacts matrix, B_{LCA} is the environmental intervention matrix of emissions per unit process of product systems (LCI), C_{LCA} is the matrix of characterization factors (part of the LCIA), and A_{LCA} is the technology matrix, which describes the flow of inputs and outputs within the system (i.e., representing the inter-process flows needed for the functioning of the product

system) (Heijungs and Suh, 2002). The inverse of the A_{LCA} matrix accounts for the interdependencies between different production processes, ensuring a consistent and scalable approach to environmental modeling. This equation forms the mathematical backbone of LCA, facilitating the transformation of inventory data into impact assessments by establishing a relationship between resource inputs and environmental emissions.

Figure 2-6 illustrates the LCA framework, representing the flow of physical inputs into production processes. On the left side, various inputs are used to generate specific outputs (A and B). The matrix, known as the LCA technology matrix A_{LCA}, details the quantity of each input required to produce outputs A and B, with columns representing the outputs and rows indicating the required input amounts.



LCA		Production of (Output)	
		A	B
Input	Input 1 (unit)	0	$-a_{1,B}$
	Input 2 (unit)	$-a_{2,A}$	0
	Input 3 (unit)	0	$-a_{3,B}$
	Input 4 (unit)	$-a_{4,A}$	$-a_{4,B}$
Output	A	1	0
	B	0	1

Figure 2-6 Representation of the LCA Technology Matrix and Process Inputs/Outputs.

III.5 Life Cycle Inventory (LCI) Databases

The accuracy and credibility of LCA depend significantly on the availability and quality of LCI data (Teng et al., 2023). These inventories capture quantified inputs and outputs of processes, such as raw material use, energy consumption, emissions to air and water, and waste generation, serving as the foundational data layer for environmental impact calculations. LCI databases allow practitioners to model both foreground and background systems in a consistent and transparent manner.

Among the most widely used and internationally recognized LCI databases is ecoinvent, which provides comprehensive and transparent datasets for more than 17,000 processes across various sectors including energy, transport, agriculture, and manufacturing. Ecoinvent is valued for its provision of elementary flows, which describe emissions and resource use in detail, enabling multicriteria environmental assessments using different LCIA methods such as ReCiPe or Impact World+ (Wernet et al., 2016).

Another major LCI provider is Sphera, which offers commercially licensed databases tailored for industrial applications. Sphera includes high-quality, peer-reviewed process data particularly useful for

sectors like automotive, chemicals, electronics, and construction. Its strong industrial partnerships and alignment with international standards make it a preferred choice for eco-design initiatives (Sphera, 2024).

LCI databases vary in terms of their geographical scope, sectoral focus, and data resolution. While some provide global, multi-sector coverage (e.g., ecoinvent, Sphera), others are designed for specific regions or industries, offering tailored inventories aligned with local practices and regulations. These specialized databases often provide more context-specific data, which is particularly useful in national or sectoral assessments (Kalverkamp et al., 2020).

In France, Agribalyse stands out as a sector-specific LCI database focusing on agricultural and food products. It offers open-access LCI data for thousands of food items and farming systems, enabling detailed environmental analysis across the agri-food chain. The database is methodologically aligned with ISO 14040 standards, and it is widely used in sustainable food labeling, policy evaluation, and life cycle-based dietary assessments (Koch et al., 2022).

In contrast to these detailed multicriteria databases, other inventories focus more narrowly on carbon accounting and provide pre-calculated emission factors rather than full process inventories. The most prominent example in France is Base Carbone®, developed by ADEME. It offers GHG emission factors (typically in kg CO_2e per unit of activity or expenditure) and is widely used in carbon footprinting, particularly for Scope 3 assessments and regulatory reporting (ADEME, 2023a). However, it generally lacks the elementary flow detail of full LCI databases.

To address growing needs for integration and simplification, ADEME has merged the Base Carbone®, primarily focused on GHG emissions, with Base Impact®, which already included life cycle impact results across multiple environmental categories (e.g., for electricity mix, or transport), into a new unified platform called Base Empreinte® (ADEME, 2023b). This consolidated database aims to provide a more comprehensive and accessible resource for environmental assessments at both the carbon and multicriteria levels.

It is important to note that databases such as ecoinvent, Sphera, and Agribalyse provide detailed LCI data based on elementary flows, enabling comprehensive multicriteria impact assessment (e.g., climate change, eutrophication, resource use, toxicity) and compatibility with multiple characterization methods. In contrast, Base Empreinte®, developed by ADEME, typically provides pre-calculated emission factors, primarily focused on carbon impacts, though some processes (e.g., electricity, transport) include additional environmental indicators.

The selection of an LCI source should be guided by the study's objective and required level of detail. Full-process LCI databases offer greater modeling flexibility and depth, particularly for product-level or comparative assessments. Simpler, factor-based inventories are more suitable for screening studies, public policy applications, or organizational reporting where data availability, time, or technical resources may be constrained (Kalverkamp et al., 2020).

III.6 Environmental Product Declarations (EPDs)

Environmental Product Declarations (EPDs) are standardized documents that transparently communicate the environmental performance of a product, based on LCA following specific product category rules. They serve as third-party–verified summaries of LCA results, ensuring credibility, comparability, and alignment with international standards such as ISO 14025 (2006) and EN 15804 (Afnor, 2019) (specific to construction products in Europe).

EPDs do not evaluate whether a product is environmentally "good" or "bad," but provide a quantitative basis for comparing similar products on environmental terms (Moshood et al., 2024). Each EPD typically includes results for multiple midpoint impact categories (e.g., global warming potential, water use, resource depletion), along with information on system boundaries (e.g., cradle-to-gate, cradle-to-grave), functional unit, and underlying assumptions.

EPDs play a key role in public procurement, green building certification systems, sustainable product labeling, and Scope 3 carbon accounting (Asdrubali et al., 2025). They represent an operational interface between LCA practitioners, manufacturers, and decision-makers across industries.

To ensure accessibility and harmonization, EPDs are stored in national and international open databases, such as:

- ECO Platform: a European initiative for harmonized EPDs across multiple sectors, ensuring mutual recognition among member programs (Eco Platform, n.d.).
- INIES: the official French database for EPDs in the building and construction sector, widely used in regulatory frameworks and building performance assessments (INIES, n.d.).
- EPD International (The International EPD® System): a global program that covers a wide range of product categories and supports multiple PCRs under a single platform (EPD International, n.d.).

These databases serve as critical repositories for structured, machine-readable environmental data, facilitating integration into digital tools, LCA software, and procurement platforms (Olanrewaju et al., 2025). In the context of this study, EPDs represent a valuable bottom-up data source, particularly when

available at the product level, allowing for more accurate and supplier-specific environmental modeling (Cimprich and Young, 2023).

III.7 Organizational Life Cycle Assessment (O-LCA)

Organizational LCA is a methodological extension of product-level LCA, developed to evaluate the cumulative environmental impacts associated with all activities, processes, and outputs of an organization over a defined reference period. Building on the ISO 14040/44 framework, O-LCA was formalized through ISO 14072 (2024), which establishes the principles and framework for applying life cycle thinking at the organizational scale. In contrast to conventional LCA, which is typically centered around a single product and a narrowly defined functional unit, O-LCA adopts the organization itself as the unit of analysis, normalizing impacts against indicators such as total revenue, or physical output.

O-LCA is inherently a multi-criteria assessment tool, capturing a broad spectrum of environmental impact categories, such as climate change, water use, resource depletion, human toxicity, and ecosystem damage, across the organization's value chain (UNEP, 2015). This makes it particularly well-suited for strategic sustainability management, environmental performance monitoring, and compliance with emerging disclosure requirements, such as those under the CSRD and the Digital Product Passports (DPP) (Max, 2025).

In contrast, the GHG Protocol, while globally recognized for GHG emissions accounting, adopts a mono-criteria approach focused solely on quantifying GHG emissions across Scopes 1, 2, and 3 (WRI and WBCSD, 2011a). While the GHG Protocol is indispensable for climate-related disclosure, it does not account for other environmental dimensions, such as water scarcity or resource depletion. O-LCA thus complements the GHG Protocol by offering a broader environmental perspective, supporting integrated sustainability strategies that go beyond carbon-centric metrics.

From a data standpoint, O-LCA accommodates bottom-up, top-down, and hybrid inventory approaches, allowing organizations to tailor their assessments based on data availability, sectoral complexity, and resource constraints (ISO 14072, 2024; UNEP, 2015), as explained in Section 2.B.III.2.

While Life Cycle Assessment (LCA) is one of the most widely used methodologies for evaluating environmental impacts within organizations, companies often rely on spend-based methods when primary physical data is unavailable (SBTi, 2024a).

IV. Environmentally Extended Input-Output (EEIO)

Spend-based approaches estimate emissions by multiplying the monetary value of purchases by emission factors, which represent the average environmental impact per unit of economic output (e.g., kg CO_2eq per € spent) (Lawson, 2024). These factors are frequently derived from EEIO models, making

EEIO a foundational, although its role is often not made explicit, component of spend-based environmental accounting (Leiminger, 2021). However, while methodologically convenient, spend-based assessments lack granularity and may introduce substantial uncertainty due to sectoral averaging and price volatility (Nakamura, 2023).

EEIO analysis, in its complete form, offers a more structured and transparent top-down modeling approach. It integrates environmental data with national or global input-output economic tables to quantify the environmental impacts of economic activities (Leontief, 1974). LCA and EEIO offer complementary strengths for emissions accounting: LCA provides detailed, product-level insights, while EEIO captures indirect impacts across entire economies and sectors, including those often missing from traditional LCA databases (e.g., services, finance). While spend-based methods use simplified EEIO data, full EEIO modeling preserves economic structure and transparency. Together, they form the basis of hybrid LCA approaches, enhancing both precision and completeness in assessing procurement-related emission (Finogenova et al., 2019).

EEIO studies typically define system boundaries based on monetary flows between industries, making them particularly suited for assessing Scope 3 emissions, consumption-based footprints, and policy interventions. Depending on the research objective, boundaries may follow production-based, consumption-based, or hybrid accounting perspectives (Sala et al., 2020). EEIO has been widely applied in carbon accounting of purchased goods and services, Material Flow Analysis (MFA) (Brunner and Rechberger, 2016), and global supply chain assessments, supporting corporate decarbonization and regulatory compliance. In environmental literature, EEIO remains a key tool for quantifying embodied environmental impacts in traded goods and indirect upstream emissions (Kitzes, 2013).

IV.1 Historical development of EEIO

The origins of EEIO analysis can be traced back to the work of Leontief (1941) on IO economics, which modeled the interdependencies between industries through economic transactions. The extension of IO models to include environmental impacts emerged in the 1970s and 1980s, as researchers sought to quantify energy consumption and pollution embedded in economic systems (Herzog, 1973; Leontief and Ford, 1972). Early studies focused on energy IO analysis, leading to the development of comprehensive EEIO databases in the 1990s, such as the U.S. Economic Input-Output Life Cycle Assessment (EIO-LCA) model by researchers from Carnegie Mellon University (Hendrickson et al., 2006).

In the 2000s, global initiatives like EXIOBASE (Tukker et al., 2013), WIOD (Timmer et al., 2015), and CEDA (Comprehensive Environmental Data Archive) (Suh, 2005) expanded EEIO applications, incorporating multiregional and sector-specific data. Today, EEIO serves as a critical tool for evaluating

trade-related environmental impacts, guiding international policies on carbon footprint reduction (Yang et al., 2022), circular economy strategies, and sustainable resource management (Donati et al., 2020).

IV.2 Key principles of EEIO

EEIO is based on several core principles that enhance its reliability and applicability in environmental assessments (Suh, 2009):

- **Monetary and Physical Input-Output Tables:** EEIO relies on national and global IO databases, which represent economic transactions and material flows across industries.
- **System-Wide Perspective:** Unlike process-based LCA, EEIO evaluates both direct and indirect environmental burdens across entire supply chains.
- **Hybridization with Process LCA:** EEIO can be integrated with process-based LCA to improve sector-specific accuracy and address data gaps in traditional LCA.
- **Data Transparency and Standardization:** EEIO models use publicly available IO data from sources such as OECD, Eurostat, and WIOD, ensuring comparability and reproducibility.
- **Scalability and Policy Relevance:** EEIO provides insights for national policy analysis, corporate sustainability reporting, and Scope 3 carbon accounting in supply chains.

IV.3 Steps of EEIO analysis

An EEIO study follows the four phases of LCA, with notable methodological differences in LCI and LCIA phases. In practice, the EEIO analysis process can be delineated into three key steps (Nakamura, 2023):

- **Data acquisition** (equivalent to inventory of activity data), where organizations collect financial expenditure records from procurement systems to capture all relevant economic activities,
- **Sectoral mapping** is conducted by assigning purchases to their respective economic sectors, allowing the application of sector-average environmental factors,
- **Emissions quantification** is performed by multiplying sector-specific emission factors with expenditure data, facilitating a macro-level assessment of indirect environmental impacts.

On a broader scale, EEIO relies on IO model construction, where inter-industry transactions are quantified using IO tables, extended with environmental coefficients (e.g., CO_2 eq per unit of economic output) (Liang et al., 2017). This is followed by EEIO-Based Environmental Impact Assessment (EIIA or EEIO-LCIA), which translates IO-derived emissions and resource use into environmental impact categories such as climate change (CO_2 emissions, carbon footprint), resource depletion (e.g., water, critical materials), and air and water pollution (e.g., SO_2, NOx, heavy metals) (Yang et al., 2017). To ensure robust impact characterization, EEIO incorporates environmental satellite accounts and LCIA

methodologies (e.g., ReCiPe 2016, TRACI, IPCC Global Warming Potential…). This comprehensive approach enables EEIO to systematically assess indirect environmental burdens across industries, supply chains, and national economies, providing critical insights for corporate sustainability strategies and regulatory decision-making (Kitzes, 2013).

IV.4 Comparison of major EEIO databases used for carbon accounting

Table 2-2 provides a comparative overview of the main EEIO databases commonly used for carbon accounting. These databases differ significantly in terms of regional coverage, sectoral and commodity granularity, and classification systems.

Table 2-2 Comparison of Major EEIO Databases Used for Carbon Accounting

Database	Coverage			Classification system	Source
	Regions	Sectors	Commodities		
Exiobase	44 countries + 5 RoW[1]	163	200	NACE[2]	(Stadler et al., 2018)
Eora	187 countries	By country (26 – 500)	-	National sectoral classification + ISIC[3]	(Lenzen et al., 2013)
GTAP	141 countries + 19 regions	65	65	HS[4] + ISIC	(Aguiar et al., 2022)
WIOD	41 countries	35	-	ISIC	(Timmer et al., 2015)

EXIOBASE is a high-resolution, environmentally extended MRIO database developed primarily for detailed environmental and economic analysis in Europe. It features a harmonized classification of over 160 sectors and products, enabling consistent cross-country comparisons and supply chain assessments. Available in industry-by-industry (ixi) and product-by-product (pxp) formats, EXIOBASE offers flexibility for different analytical purposes. The ixi format models transactions between industries, capturing how outputs from one industry serve as inputs to another, while the pxp format traces the flow of specific products (commodities) through the economy. Within the European context, EXIOBASE is particularly suited for environmental footprinting and procurement analysis, as it enables

[1] RoW: Rest of the World, summarizing the remaining countries in Europe, Asia, Africa, the Americas, and the Middle East.

[2] NACE: in English « Classification of Economic Activities in the European Community » | in French « Nomenclature des Activités Économiques dans la Communauté Européenne » .

[3] ISIC: International Standard Industrial Classification

[4] HS: Harmonized System Classification

more precise tracking of impacts associated with individual goods and services.

In contrast, Eora includes a large number of countries but relies on nationally reported input–output tables with sectoral structures that vary significantly between countries, ranging from as few as 26 to over 500 sectors. As a result, commodity classifications in Eora are not standardized across countries, limiting direct comparability at the product level. GTAP, although widely used in economic modeling and trade analysis, uses an aggregated set of 65 sectors and commodities, based on its own classification system aligned with HS and ISIC codes. However, it does not provide product-level detail in the same sense as EXIOBASE. WIOD offers harmonized sectoral data across 41 countries but focuses on industry-level classifications (using ISIC codes), without specifying a standardized product list.

These structural differences have direct implications for the level of detail and comparability achievable in carbon accounting studies, especially when assessing Scope 3 emissions or conducting hybrid life cycle assessments.

It is important to note that some widely used carbon accounting database, such as CEDA (Comprehensive Environmental Data Archive), are based on emission factor datasets derived from EEIO modeling, but do not constitute EEIO databases themselves. CEDA provides pre-calculated emission factors linked to different industry sectors, making it useful for spend-based footprinting, but it lacks the underlying input-output transaction tables typically found in full EEIO models (Watershed, 2024).

A core feature of EEIO databases is their integration with environmental satellite accounts, which link economic transactions to environmental flows (e.g., GHG emissions, energy use, water withdrawal). These extensions are essential for enabling carbon and multi-impact assessments, and their quality and availability vary across databases (Yang et al., 2017). This variation affects their suitability for Scope 3 accounting and hybrid modeling.

In addition to global EEIO databases, some countries, such as France, also publish region-specific input-output tables, such as those from INSEE (2022). While these national datasets can be useful for capturing localized economic structures, they often lack the sectoral and product-level granularity required for detailed carbon accounting. For instance, INSEE's framework includes only 37 aggregated sectors, compared to EXIOBASE's 163 sectors and over 200 products.

EXIOBASE also adopts the NACE classification system, the European statistical classification of economic activities. NACE's four-level hierarchical structure allows classification from broad sectors (e.g., manufacturing) down to specific activities (e.g., manufacture of office machinery), and aligns closely with France's NAF system. This alignment facilitates the mapping and integration of national

data into broader EU-level analyses (European Commission, 2022).

Due to EXIOBASE's high sectoral resolution, standardized classification, harmonized environmental extensions, and strong compatibility with European statistical systems, it is used as the foundational database for the methodological development presented in Chapter 4.

IV.5 Computational Framework of EEIO

The computational framework of EEIO quantifies environmental impacts based on economic flows and environmental extensions. The fundamental equation of EEIO, as expressed in Equation 2-2, is given by:

$$e_{EEIO} = B_{EEIO} \times C_{EEIO} \times (\mathrm{I} - A_{EEIO})^{-1}$$

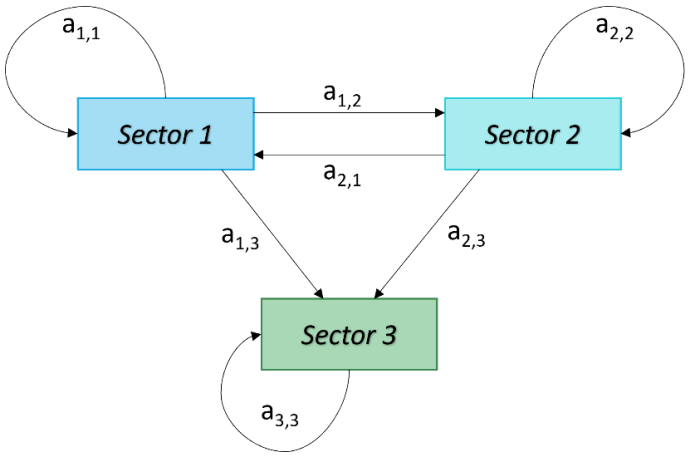
Equation 2-2 Computational Equation of EEIO

where e_{EEIO} represents the environmental impacts matrix, B_{EEIO} is the environmental intervention matrix of emissions per unit process of product systems (LCI), C_{EEIO} is the matrix of characterization factors (part of the LCIA), and A_{EEIO} is the technology matrix, which describes the flow of inputs and outputs within the system (i.e., representing the inter-process flows needed for the functioning of the product system). The Leontief inverse of AEEIO, also called the total requirements matrix, is in the form of total dollars of an input required directly and indirectly to produce a dollar of an output. Calculated by $(I- A_{EEIO})^{-1}$, where I is the identity matrix (Leontief, 1974).

This equation reflects the mathematical backbone of EEIO, enabling economy-wide environmental assessments by linking industrial production with emissions and resource use. Unlike process-based LCA, which relies on specific process datasets, EEIO leverages monetary flow models, making it highly scalable for macro-level sustainability analysis.

Figure 2-7 illustrates the EEIO framework, depicting interdependencies between three sectors through the exchange of inputs and outputs. On the left side, arrows indicate the flow of resources or products between sectors, with $a_{i,j}$ representing the quantity transferred from Sector i to Sector j. On the right, the technology matrix A_{EEIO} presents the EEIO model (€ per €), capturing inter-sectoral monetary flows where $a_{i,j}$ denotes the financial exchange from Sector i to Sector.

EEIO analysis provides a holistic, macroeconomic approach to environmental impact assessment, complementing process-based LCA by capturing indirect impacts and supply chain interdependencies. While EEIO excels at economy-wide and Scope 3 assessments, its integration with hybrid LCA methods offers a more comprehensive sustainability evaluation framework, supporting businesses, policymakers, and researchers in advancing environmental decision-making.



EEIO (€/€)		Output		
		Sector 1	Sector 2	Sector 3
Input	Sector 1	$a_{1,1}$	$a_{1,2}$	$a_{1,3}$
	Sector 2	$a_{2,1}$	$a_{2,2}$	$a_{2,3}$
	Sector 3	0	0	$a_{3,3}$

Figure 2-7 Representation of the EEIO Technology Matrix and Process Inputs/Outputs.

IV.6 Overview of EEIO Computational Tools

In line with the observations of Stadler (2021), unlike LCA (which benefits from established tools like Brightway and openLCA), the field of Multi-Regional Input-Output (MRIO) analysis lacks a comparable suite of robust, general-purpose software tools. Despite its growing importance in academic research and policy development, MRIO implementation often relies on custom-built scripts and non-standardized approaches, limiting reproducibility, transparency, and methodological coherence across studies.

To address this methodological gap, several computational tools have been developed to facilitate the use of EEIO databases in environmental footprinting and policy analysis. These tools vary in functionality, architecture, and compatibility with MRIO datasets. Among the most commonly used are:

- **Pymrio** (Stadler, 2021)**:** a Python-based library specifically designed for handling MRIO datasets, particularly EXIOBASE. It offers a well-structured object-oriented interface for importing, manipulating, and analyzing MRIO systems. Key features include:
    - Native compatibility with EXIOBASE formats (e.g., .pxp, .ixi),
    - Built-in support for Leontief modeling, footprint calculations, and satellite data integration,
    - Integration with characterization factors for environmental impact assessments,
    - Designed for reproducibility, transparency, and automation in research and policy workflows.

  Its seamless integration with the scientific Python ecosystem (NumPy, Pandas, Matplotlib) makes it ideal for developing scalable and flexible applications, such as automated Scope 3 assessments or LCA extensions.

- **PyIO** (Nazara et al., 2003)**:** One of the earliest standalone packages for IO analysis. While historically significant, it is no longer maintained, is incompatible with Python 3, and does not support current MRIO datasets. Its last update was in 2011, and it lacks support for standardized database formats, limiting its practical use today.
- **MRIOLab suite** (Lenzen et al., 2017)**:** This framework focuses on the compilation of MRIO tables rather than analysis. While it includes some functions for MRIO modeling, these are tightly coupled with its internal data structure and not well-suited for analyzing MRIO datasets compiled externally (e.g., EXIOBASE, Eora, WIOD), thus reducing flexibility and transferability.

Among the available options, pymrio stands out for its purpose-built design, alignment with EXIOBASE, and support for transparent, reproducible environmental accounting workflows (Stadler, 2021). These features underpin its selection in this study as the core computational tool for implementing the EEIO model.

IV.7 Differences Between EEIO and LCA

LCA and EEIO analysis are two widely used methodologies for quantifying environmental impacts. While both approaches aim to quantify resource use and emissions, they differ in scope, data sources, and application. Table 2-3 summarizes the main differences.

Both methodologies rely on a matrix (B) that quantifies environmental flows, such as greenhouse gas (GHG) emissions, either at the process or product level in LCA or at the sectoral level in EEIO, and a matric (C) that represents the matrix of characterization factors, to determine the environmental impacts (e) associated with the system under study. These environmental flows can be represented in physical units (applicable to both LCA and EEIO) or monetary units (only in EEIO). Additionally, the technology matrix (A) captures the inputs and outputs of production processes, serving as a fundamental component in both approaches, though its structural formulation differs between LCA and EEIO. The key difference between the technology matrix A_{LCA} and A_{EEIO} are depicted in Figure 2-8.

LCA		Production of (Output)	
		Ready-Mix Concrete (m3)	*Concrete Used for Blocks (m3)*
Input	*Cement (kg)*	- 300	- 250
	Water (L)	- 175	-150
	Aggregates (kg)	- 1300	- 1400
	Additives (kg)	-5	- 3
	Electricity (kWh)	-5	- 4
Output	*Ready-Mix Concrete (m3)*	1	0
	Concrete Used for Blocks (m3)	0	1

EEIO (€/€)		Output			
		Extraction	*Manufacturing*	*Transport*	*Construction*
Input	*Extraction*	0.35	0.12	0.12	0.12
	Manufacturing	0.02	0.02	0.02	0.02
	Transport	0.06	0.06	0.06	0.06
	Construction	0.03	0.03	0.03	0.03

Figure 2-8 Difference Between Technology Matrices of EEIO and LCA

Table 2-3 Key Differences Between EEIO Analysis and LCA

Features		EEIO	LCA
Analytical scope	Scope	Economy-wide, industry-level	Product-specific, process-level
		Macroscopic level	Microscopic level
	System Boundaries	Global, national, or industry-based	Cradle-to-gate, cradle-to-grave, cradle-to-cradle
	Functional Unit	$1M of output, kg of material	Defined per product system (e.g., 1 kg of product)
Data	Data Source	Input-output tables (monetary, physical)	Foreground & background LCI databases
	Availability	Generally good, as it uses existing economic and environmental datasets.	Variable and can be limited by the specificity of required data.
	Quality	More consistent but may lack detail and specificity.	Dependent on the sources and precision of collected data.
	Completeness	More complete at a macro level, but less detailed	Often requires significant effort to achieve, may have gaps
	Requirement	Uses aggregated economic data and environmental coefficients for entire sectors.	Requires specific data for each process in the life cycle of the product.
	Granularity	Low granularity, broader sectoral information.	High granularity with detailed process-level information.
Truncation error		Lower, as it captures economy-wide interactions,	Potentially significant, as it may not cover all upstream and downstream processes (cut-offs)
Double counting		Potential, as some emissions may be included at multiple economic transaction points	Less prone, as system boundaries and flows are explicitly defined per process
Strengths		Captures indirect emissions and economy-wide interactions, simple and easy to implement	High granularity for product-level assessments
Limitations		Lacks process-level detail, potential aggregation bias	Data-intensive, time-consuming, limited to defined system boundaries

In LCA, the technology matrix A_{LCA} organizes processes into columns, with negative values representing inputs (e.g., –300 kg of cement) and positive values indicating outputs (e.g., 1 m³ of ready-mix concrete), as illustrated in Figure 2-6. All entries in A_{LCA} are expressed in physical units and reflect the material and energy flows between processes. Importantly, A_{LCA} is not necessarily a square matrix, and the diagonal values do not carry specific interpretive meaning; they are simply mathematical artifacts in the system of equations used (see Equation 2-1).

In contrast, EEIO analysis uses a different matrix structure A_{EEIO}. Each column of A_{EEIO} describes the production recipe for a given sector, specifying the monetary value of inputs required to produce one unit of output (e.g., producing €1 of construction output requires €0.02 of manufactured products), as

shown in Figure 2-7. Unlike A_{LCA}, A_{EEIO} is a square and symmetric matrix, and its diagonal elements represent self-consumption, i.e., the amount a sector consumes of its own output during production (see Equation 2-2).

The sources of these matrices also differ significantly. A_{EEIO} is derived from national input-output (IO) tables published by statistical agencies, ensuring broad sectoral coverage and economy-wide completeness. In contrast, A_{LCA} is manually compiled by LCA practitioners using data from specific unit processes. While this can provide high granularity and detail, it often lacks the completeness and consistency required to represent all relevant activities within a system boundary.

V. Hybrid Methods

Hybridization of LCA and EEIO aims to bridge the gap between process specificity and economy-wide completeness by integrating detailed life cycle inventory data with the systemic coverage of input-output analysis (Suh and Huppes, 2000). The primary objective of hybridization is to reduce truncation errors inherent in process-based LCA by incorporating upstream supply chain impacts captured in EEIO models (Suh et al., 2004). Additionally, hybrid approaches enhance the granularity and accuracy of EEIO results by supplementing sector-aggregated data with product-specific inventories (Lenzen et al., 2013). This integration enables a multi-scale perspective, allowing for both macro-level policy analysis (e.g., national carbon footprint assessments) and micro-level decision-making (e.g., product design improvements) (Hertwich and Peters, 2009). Hybrid models also facilitate comprehensive Scope 3 emissions accounting, which is particularly relevant for corporate sustainability reporting and regulatory compliance (Allen et al., 2021). Furthermore, hybridization improves the robustness of environmental assessments by aligning monetary and physical data streams, ensuring consistency in cross-sectoral comparisons (Suh and Huppes, 2005). By leveraging the computational strengths of both LCA and EEIO analysis, hybrid models provide a more holistic and scalable framework for evaluating environmental impacts across industries, supply chains, and economies, and improve comprehensiveness, accuracy, and applicability of environmental impact assessments (Weidema and Wesnæs, 1996).

In academic literature, several distinct hybridization techniques have been developed, each differing in how process-based and IO-based data are integrated into the overall assessment framework. Below are the key hybridization approaches found in literature.

V.1 Historical Development of hybrid models

The development of hybrid models has progressed over several decades, driven by the need to overcome the limitations of conventional assessment methods. Table 2-4 highlights key milestones in the evolution of hybrid methodologies, documenting seminal contributions that laid the groundwork

for their conceptual and mathematical foundations. These pioneering efforts have collectively advanced the precision and scope of environmental assessments by integrating the strengths of process-based and input-output approaches.

Table 2-4 Pioneering Contributions to Hybrid Methods

Year	Authors	Contribution
1978	Bullard et al.	Introduced the concept of a hybrid model for energy analysis by integrating process and input-output data, leading to the Tiered Hybrid LCA (THL) model.
1997	Treloar	Proposed an input-output-based hybrid analysis and introduced the concepts of input-output matrix disaggregation and Patch Exchange (PXC).
1999	Joshi	Developed the Matrix Augmentation (MA) method, allowing the inclusion of a hypothetical sector or the disaggregation of an existing one within the matrix.
2000	Suh and Huppes	Established the mathematical framework for the Integrated Hybrid LCA (IHL) model.
2009	Lenzen & Crawford	Improved and advanced PXC's hybridization techniques.

Today, Hybrid methods continue to evolve, playing a crucial role in environmental impact assessment and sustainability strategies by bridging gaps between macroeconomic modeling and detailed product-level analyses.

V.2 Tiered Hybrid LCA (THL)

The Tiered Hybrid Life Cycle Assessment (THL) method integrates process-based LCA with EEIO analysis to expand system boundaries and incorporate upstream environmental impacts that traditional process-based analysis alone may overlook. Originally developed by Bullard et al. (1978) and refined by Heijungs and Suh (2002), classic THL enables researchers to define the boundary between process and input-output data, tailoring the method to the specific needs of a given study. This approach is particularly useful when detailed process data is available for some life cycle stages, while EEIO coefficients fill data gaps for complex or indirect upstream inputs, such as financial services, capital goods, or Scope 3 emissions.

For instance, some studies apply PLCA to use, disposal, and high-contribution processes, while relying on EEIO data for upstream life cycle stages such as material extraction and supply chain emissions, as illustrated in Figure 2-9 (Model a) (Crawford et al., 2018). This ensures that core production processes are modeled with high specificity, while broader supply chain emissions, often difficult to capture through PLCA alone, are still accounted for. Similarly, in corporate carbon footprinting, classic THL can

be structured to apply PLCA data to Scope 1 and Scope 2 emissions, while EEIO data is used for Scope 3 emissions, as shown in Figure 2-9 (Model b) (García-Alaminos et al., 2022). In practice, the application of classic THL varies widely: some studies use input-output data for nearly all phases except end-of-life, while others apply it only to fill gaps where detailed process data is unavailable (Crawford et al., 2018).

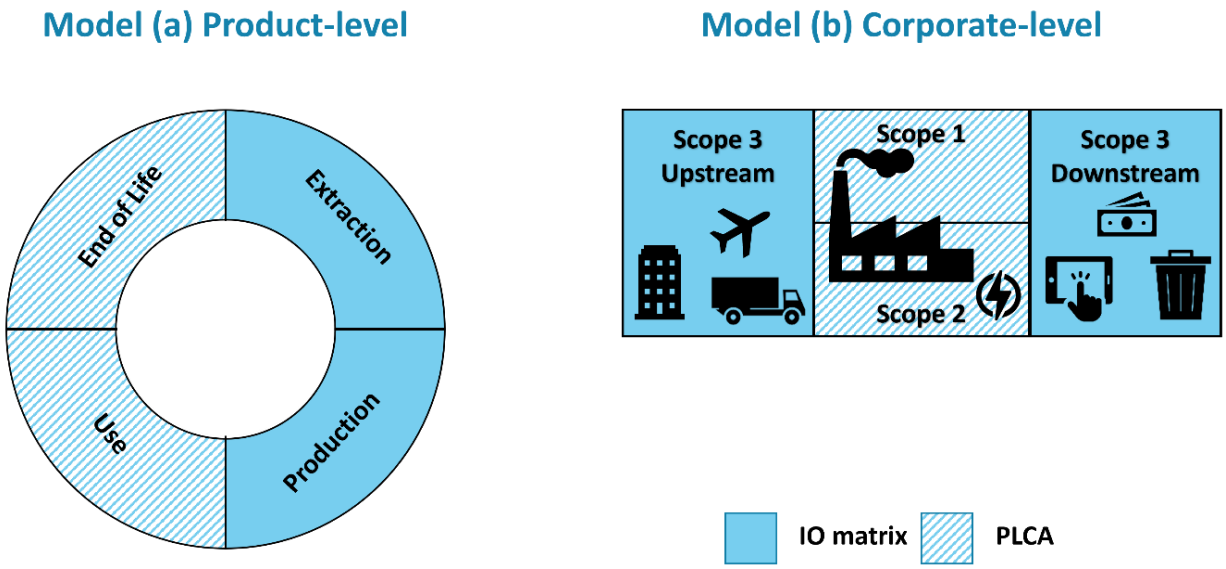


Figure 2-9 Graphic Representation of Tiered Hybrid LCA (THL) (adapted from (Hagenaars et al., 2025))

One of classic THL's main advantages is its speed and flexibility, making it especially valuable for rapid assessments and preliminary decision-making (Strømman et al., 2009). It is widely adopted across various sectors due to its adaptability and ease of use, particularly in situations where detailed life cycle inventories are partially available.

However, classic THL has several limitations. A major drawback is the lack of a consistent computational structure, which can hinder reproducibility and transparency. This inconsistency becomes especially problematic in comparative studies where methodological uniformity is crucial. Additionally, classic THL is prone to double-counting, as overlapping PLCA and EEIO data can inflate results if not carefully reconciled (Crawford et al., 2018). These limitations often make it unsuitable for rigorous comparative assessments across products or sectors.

To overcome the limitations of classic THL, researchers such as Agez et al. (2020a) and Yu and Wiedmann (2018) have developed a more structured and consistent approach, notably the Systematic Tiered Hybrid LCA (STHL) method. Conceived as an extension of classic THL, STHL enhances methodological rigor by reducing truncation errors and minimizing double counting through a transparent and reproducible workflow. It integrates process and input-output data systematically, beginning with the construction of a technology matrix from process-level data. Input-output data is

then used to fill supply chain gaps, and systematic corrections are applied to avoid overlap between PLCA and EEIO contributions.

Recent advances, such as those by Agez et al. (2020), have improved the computational accuracy of STHL, enabling full dataset hybridization and large-scale industrial assessments. This method is particularly suited to applications requiring high data completeness and potential automation.

Compared to classic THL, Systematic THL better addresses truncation errors, ensures reproducibility, and can be partially automated, offering a balanced solution between accuracy and efficiency. However, its greater complexity limits its adoption in areas like procurement, where simpler methods are often preferred.

In summary, while classic THL remains useful for flexible, rapid assessments, Systematic THL represents a key methodological advancement, especially valuable for studies requiring precision, consistency, and traceability.

V.3 Path Exchange Hybrid Method (PXC)

The Path Exchange Method (PXC) is a hybrid approach in Life Cycle Assessment (LCA) that enhances the accuracy of supply chain footprinting by selectively replacing aggregated EEIO pathways with detailed process-based LCA data. Originally introduced by Treloar (1997) and later formalized by Lenzen and Crawford (2009), this method enables the mathematical disaggregation of an input-output matrix, allowing for the identification and modification of specific supply chain pathways while maintaining system boundary completeness (Figure 2-10). By tailoring supply chain components using available process data, PXC refines the representation of indirect environmental impacts in EEIO models, making it a valuable tool for hybrid LCA applications.

One of the key strengths of the PXC method is its ability to improve specificity by introducing process-level alternatives for key supply chain activities, rather than relying solely on sector-average EEIO coefficients. This is particularly relevant in industrial emissions modeling, where broad input-output-based emission factors may lack resolution (Crawford et al., 2018). For instance, rather than using a generic "iron and steel" EEIO sector, PXC enables the integration of granular LCA datasets covering blast furnaces, electric arc furnaces, and steel rolling operations. A notable application of this approach was demonstrated by Baboulet and Lenzen (2010) in their assessment of a university's supply chain performance, where certain pathways were adjusted to reflect alternative scenarios.

Additionally, PXC ensures system boundary completeness while allowing for targeted modifications, making it particularly valuable in benchmarking, product comparisons, and policy-driven environmental assessments (Stephan et al., 2019).

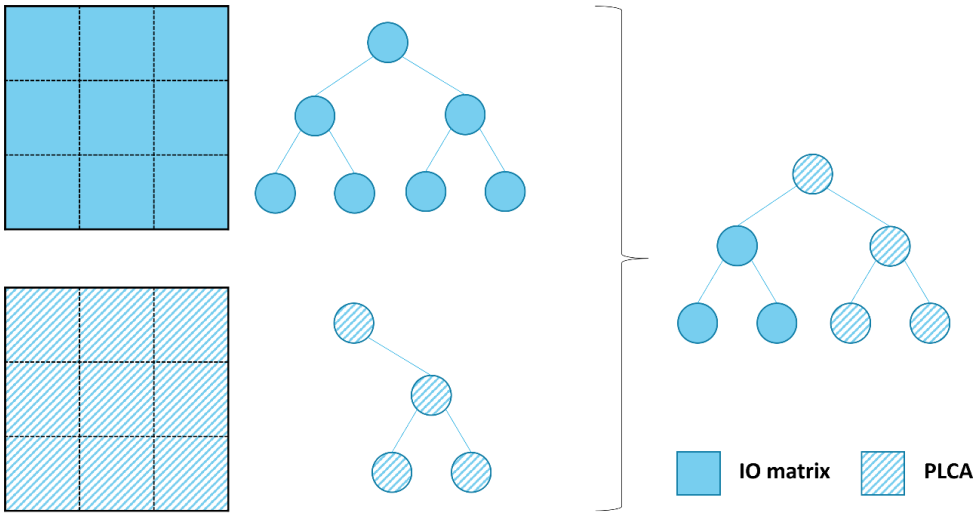


Figure 2-10 Graphic Representation of Path Exchange Hybrid Method (PXC) (adapted from (Hagenaars et al., 2025))

Beyond improving specificity, PXC also offers enhanced consistency and transparency by ensuring that process and input-output data are methodologically aligned, avoiding double-counting errors that may arise in other hybridization approaches. Another advantage is its flexibility in incorporating any type of process data, meaning it can be applied across various industries and product systems. Furthermore, by replacing the most significant nodes in the supply chain with detailed LCA data, PXC ensures that key environmental hotspots are accurately represented (Hagenaars et al., 2025).

However, PXC also has certain limitations. One of its main weaknesses is its time-intensive nature and computational complexity, requiring expert-level knowledge of both PLCA and EEIO models. Since PXC forces PLCA data into the matrix format of EEIO data, the method requires extensive data manipulation and matching, which can make implementation challenging. Furthermore, PXC remains partially dependent on IO-based sectoral averages where detailed process data is unavailable, potentially limiting its accuracy in cases where process data is incomplete (Guan et al., 2016). Additionally, PXC assumes that IO and PLCA are representations of the same supply chain, which may introduce uncertainties when there are structural differences between the two datasets.

Despite these limitations, advancements in automation and machine learning are helping to streamline the PXC approach, making it more accessible for large-scale sustainability evaluations and policy-driven environmental modeling (Liou, 2023). As computational tools evolve, PXC is expected to become an increasingly valuable technique for refining hybrid LCA models.

V.4 Matrix Augmentation (MA)

The Matrix Augmentation (MA) method is a hybrid approach that expands the traditional Environmentally Extended Input-Output (EEIO) technology matrix by integrating Process-Based LCA (PLCA) data, thereby enhancing sectoral resolution (Joshi, 1999). This method is particularly useful for

disaggregating broad IO sectors into more specific sub-sectors or for introducing entirely new sectors into the IO matrix, allowing for a more precise assessment of specific products, industries, or emerging technologies. By modifying the existing IO structure, MA helps reduce aggregation errors in conventional EEIO models while preserving system-wide consistency.

One key application of MA is sector disaggregation, where a broad aggregated IO sector is divided into more detailed sub-sectors based on economic output, process data, or other relevant indicators (Figure 2-11.a). For example, Wiedmann et al. (2011) applied MA to disaggregate the electricity sector to better assess wind power generation, ensuring that the environmental impacts of wind energy were not overshadowed by other sources of electricity. This approach reduces aggregation errors found in conventional EEIO models, making assessments more industry-specific and policy-relevant. A second application of MA is sector creation, where a new theoretical sector is introduced into the IO matrix to model emerging technologies or products not yet represented in national or global IO tables, as seen in Figure 2-11.b. This method was used by Malik et al. (2015) to incorporate biofuels into Australia's IO framework, ensuring that their production and environmental impacts could be accurately assessed. In this case, process-based LCA data was integrated to model the physical input requirements of the newly created sectors, while EEIO coefficients were used to estimate non-physical inputs such as financial services or indirect supply chain emissions.

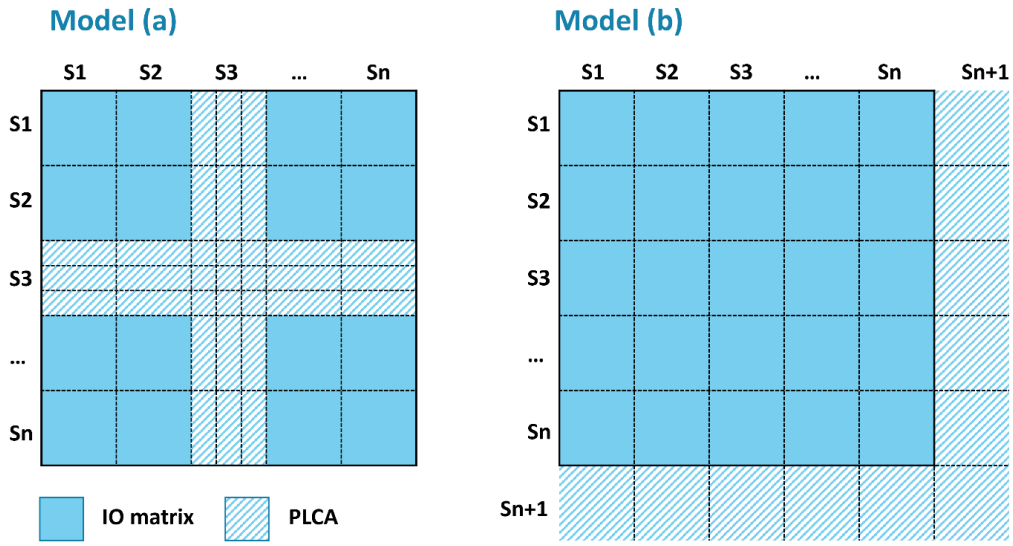


Figure 2-11 Graphic Representation of Matrix Augmentation (MA) Hybrid Method (adapted from (Crawford et al., 2018))

One of the key strengths of MA is its ability to improve data granularity while preserving the system-wide completeness of EEIO. By allowing researchers to isolate product-specific environmental impacts within highly aggregated IO sectors, MA enhances the accuracy of impact assessments, making it particularly useful for case studies and policy analysis. Additionally, MA requires relatively little PLCA knowledge, making it accessible to researchers and practitioners with limited experience in process-

based LCA. Furthermore, its small data dependency allows it to be applied even when detailed process inventories are unavailable, and it can incorporate any type of process data, increasing its flexibility across different industries (Jiang et al., 2014).

Some studies have also streamlined MA by incorporating object-oriented programming and automated sector-matching techniques, improving scalability and computational efficiency (Ghosh and Bakshi, 2020).

However, MA has notable limitations. A primary drawback is that aggregation errors are only partially addressed, as disaggregation typically occurs at the first level of assessment, while upstream processes remain aggregated (Zafrilla et al., 2014). This means that certain upstream emissions and supply chain interactions may still be misrepresented. Additionally, many studies scale the outputs of new or disaggregated IO sectors based on the original sector's economic structure (Wiedmann et al., 2011), which may limit the benefits of MA when the new sector has significantly different input-output relationships. This assumption can introduce bias and uncertainty, particularly in cases where process-level differences between sub-sectors are large (Salemdeeb et al., 2017). Another notable limitation is that MA neglects End-of-Life (EoL) impacts, as IO tables typically focus on economic transactions rather than waste treatment or disposal. Furthermore, since the augmented sectors are often scaled to the original sector's sales structure, the full environmental implications of new or emerging technologies may not be accurately reflected.

Despite its limitations, MA remains a valuable hybridization method for improving sectoral specificity in EEIO models, particularly in fast project screening and case study applications. As new automation techniques and data sources continue to enhance hybrid LCA methodologies, MA is expected to play a growing role in assessing novel industries, emerging technologies, and underrepresented economic activities within environmental sustainability research. With further refinements in sector disaggregation techniques and improved integration of physical data, MA has the potential to increase the accuracy and applicability of hybrid LCA models, making it a powerful tool for sustainability assessments and policy-driven decision-making.

V.5 Integrated Hybrid LCA (IHL)

The Integrated Hybrid Life Cycle Assessment (IHL) method is the most methodologically consistent hybrid approach, as it fully integrates PLCA and EEIO data into a single mathematical framework (Suh and Huppes, 2000). Unlike other hybrid models that handle PLCA and EEIO data separately, IHL establishes a fully integrated system of equations, ensuring internal consistency and comprehensive system coverage. By leveraging the Leontief inverse $(I - A)^{-1}$ across both datasets, this approach effectively bridges process-level detail with economy-wide data. The integration is facilitated through

upstream and downstream cut-off matrices (Figure 2-12), which serve as linking vectors—representing the flow of inputs from the input-output framework into process models (upstream cut-off) and the allocation of process-based outputs to IO sectors (downstream cut-off).

One of the key applications of IHL is in large-scale environmental assessments, where both micro-level detail and macro-level system completeness are required. For example, national carbon accounting models utilize IHL to merge product LCA data with EEIO-based trade and consumption models, enabling a comprehensive evaluation of national and sectoral greenhouse gas emissions. Similarly, energy transition studies integrate PLCA-based models for renewable energy technologies with EEIO-driven macroeconomic models, providing insights into the systemic impacts of decarbonization strategies (Acquaye et al., 2011). This combination of fine-grained LCA data with the broad coverage of EEIO makes IHL particularly useful for supply chain resilience modeling, policy development, and strategic sustainability planning.

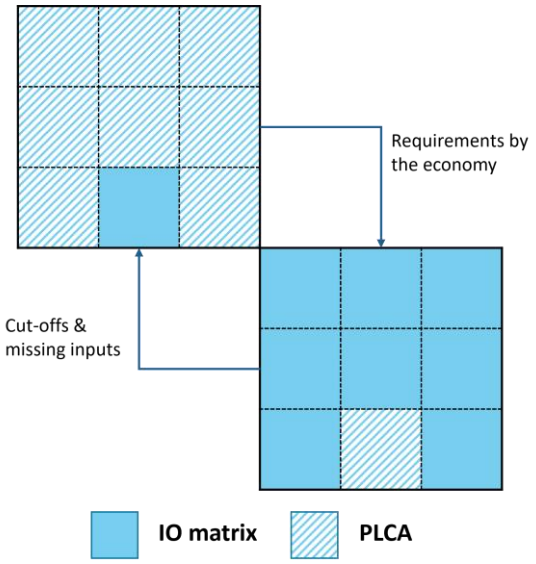


Figure 2-12 Graphic Representation of Integrated Hybrid LCA Method (IHL) (adapted from (Hagenaars et al., 2025))

A major strength of IHL is its increased accuracy, precision, and transparency compared to other hybrid LCA methods (Heijungs et al., 2022). By integrating PLCA and EEIO data within a single framework, it eliminates inconsistencies arising from separately handling process- and sector-level data, ensuring a more robust representation of environmental burdens (Suh, 2004). Additionally, IHL reduces background truncation errors, as it systematically accounts for all supply chain interactions, rather than relying on fragmented data sources (Palma-Rojas and Nogueira, 2015).

However, IHL also presents significant challenges. The method is computationally demanding, requiring extensive data harmonization and sector-process alignment (Bush et al., 2014). Moreover, correcting for double-counting is more complex than in other hybrid methods, as the full matrix-based

integration increases the likelihood of overlapping system boundaries. The time and expertise required for implementation also make IHL less accessible for smaller-scale studies or organizations with limited computational resources (Dadhich et al., 2015). Furthermore, while IHL effectively hybridizes background system truncation, it does not inherently address foreground system limitations, meaning that some process-level granularity may still be needed for highly detailed product-level assessments.

Despite its complexity and high computational cost, IHL remains the gold standard for hybrid LCA, offering unmatched consistency and system-wide completeness. As advances in automation, machine learning, and data harmonization continue to evolve, IHL is expected to become more scalable, making it a critical tool for nationwide sustainability assessments, corporate carbon footprinting, and policy-driven environmental strategies.

Each hybridization method offers a balance between system completeness and resolution, making them suitable for different applications. Tiered Hybrid LCA approach is widely used for product-level and corporate assessments, while Integrated Hybrid LCA (IHL) provides the most consistent methodology for large-scale policy and supply chain studies. The Path Exchange and Matrix Augmentation methods serve as intermediate solutions, enhancing sectoral granularity while maintaining economy-wide completeness. The choice of hybridization method depends on data availability, computational resources, and the specific research or business objective. Future advancements in machine learning, big data integration, and automated hybridization techniques will further improve the accuracy and scalability of HLCA approaches.

V.6 Comparative Overview of Hybrid Methods for Procurement Applications

Table 2-5 compares key Hybrid LCA methods, summarizing their principles, structures, strengths, and limitations to support method selection in procurement-related environmental assessments.

While hybrid models address limitations in environmental impact accounting by combining process and economic models, they do not cover social dimensions. The following section introduces Social Life Cycle Assessment (S-LCA), a complementary approach that accounts for human and societal impacts across supply chains.

Table 2-5 Detailed Comparison of Hybrid LCA Methods and Their Applications in Procurement

Method	Classic THL	Systematic THL (STHL)	Path Exchange (PXC)	Matrix Augmentation (MA)	Integrated Hybrid LCA (IHL)
Principle	Combines PLCA for detailed stages and EEIO for missing data; user-defined boundary.	Structured version of THL; corrects truncation errors and avoids double-counting.	Replaces specific IO pathways with process data for key supply chain nodes.	Disaggregates IO sectors or creates new sectors to improve granularity.	Fully integrates PLCA and EEIO into a single mathematical framework using cut-off matrices.
Origin & Key Contributors	Bullard et al. (1978); Heijungs & Suh (2002)	Heijungs & Suh (2002); Suh & Huppes (2000); Agez et al. (2025)	Treloar (1997); Lenzen & Crawford (2009)	Joshi (1999) ; Wiedmann et al. (2011) ; Malik et al. (2015)	Suh & Huppes (2000) ; Suh et al. (2004) ; Heijungs & Suh (2002)
Main Strengths	Fast, flexible, reduces truncation errors; widely used.	Transparent, reproducible, partially automatable; suitable for benchmarking.	Enhances specificity; adaptable to supply chain changes; avoids double-counting.	Improves sector resolution; enables scenario modeling; low PLCA expertise needed.	Most comprehensive and consistent; captures all upstream and downstream impacts.
Limitations	Prone to double-counting; lacks standardization; limited reproducibility.	More complex than Classic THL; limited use in procurement.	Computationally complex; requires large datasets; assumes supply chain equivalence.	Scale distortions possible; upstream emissions still aggregated; lacks EOL modeling.	Highly data-intensive; complex to model; difficult to modify once built.
Truncation Error Handling	Partial correction; limited to where EEIO is used	Systematic correction using matrix algebra and gap-filling	Corrects key pathways manually, based on disaggregation	Reduces errors by refining IO sectors or adding new ones	Eliminates truncation errors through full system integration
Double Counting Risk	High without manual adjustments	Low; managed via systematic matrix corrections	Low; due to pathway substitution logic	Medium: depends on calibration of added/disaggregated sectors	Low if cut-off matrices are properly defined

Method	**Classic THL**	**Systematic THL (STHL)**	**Path Exchange (PXC)**	**Matrix Augmentation (MA)**	**Integrated Hybrid LCA (IHL)**
Best Use Cases	Supplier assessments, public procurement, rapid footprinting.	Policy benchmarking, Scope 3 estimation, upstream data gap filling.	Comparing suppliers/regions, identifying emission hotspots in supply chains.	Emerging technologies, procurement of novel materials, wind/solar assessments.	National GHG inventories, full corporate carbon footprints, energy transition studies.
Procurement Applications	Identify high-impact suppliers and stages; support sourcing decisions.	Evaluate suppliers across tiers; prioritize environmental risk mitigation.	Compare environmental impact of supplier or regional options.	Add detail on suppliers' energy use, emissions; improve assessment precision.	Evaluate suppliers using multi-criteria (environmental, social, economic) metrics.
Automation Potential	Low – manual boundary selection, prone to inconsistencies	Moderate to High – structured workflow, compatible with partial automation tools (e.g., pylcaio)	Low – manual disaggregation and path replacement required	Low – manual sector creation/disaggregation and calibration	Low to Moderate – high complexity but potential for automation via structured frameworks
Computational Complexity	Low – minimal modeling structure, fast to compute	Moderate – structured matrix operations and corrections	High – path-level manipulation, complex algebra	Moderate – requires matrix restructuring but manageable	Very High – full matrix integration and advanced algebra
Data Requirements	Moderate – partial process data and sector-level IO data	High – complete process data, sector mapping, cut-off matrices	High – detailed path-level data and disaggregated IO	Moderate – IO data plus any additional disaggregation or new sector data	Very High – detailed LCI, IO tables, and defined cut-off matrices
Typical Application Domains	Public procurement, transport studies, energy systems	Policy development, benchmarking, national LCI updates	Construction, university operations, energy supply chains	Renewable energy, circular economy, industrial materials	National carbon inventories, industrial decarbonization plans

VI. Social Life Cycle Assessment (S-LCA)

Social Life Cycle Assessment (S-LCA) is a method that enables the evaluation of the social impact of products and services along their life cycle (UNEP, 2020). Social impacts can be defined as consequences of positive or negative pressures on social endpoints related to an area of protection, such as the well-being of stakeholders or social justice (Valdivia et al., 2021). These impacts are assessed across the life cycle stages of a product or service, from raw material extraction to end-of-life, in alignment with life cycle thinking principles.

S-LCA plays a critical role in extending life cycle thinking beyond environmental assessment by explicitly incorporating social and societal dimensions. It fosters a systems-based understanding of social responsibility, enabling organizations to identify potential social risks, inequalities, and areas of positive contribution along increasingly complex global value chains (Bouillass et al., 2021). Through this integrative lens, S-LCA ensures that sustainability-related decisions are made with due consideration for human welfare and community impacts.

Unlike its environmental counterpart, LCA, which quantifies environmental burdens, S-LCA focuses specifically on human and societal impacts. It employs a range of qualitative, semi-quantitative, and context-sensitive indicators to capture social performance (UNEP, 2020). The nature and interpretation of these impacts are shaped by the socio-economic, regulatory, and cultural context in which the product or service is situated.

S-LCA is increasingly recognized as a complementary approach to LCC and environmental LCA. While LCA and LCC tend to be more quantitative and data-driven, S-LCA remains more qualitative and normative in nature, reflecting the complexity and subjectivity inherent in assessing social phenomena (Valdivia and Sonnemann, 2024). Nonetheless, their combined use offers a robust basis for informed, balanced, and ethically grounded decision-making, particularly in the context of sustainable procurement and supply chain management (Lehmann, 2023).

In recent years, S-LCA has attracted growing attention due to rising global expectations around human rights due diligence, fair labor practices, and ethical sourcing. However, despite its conceptual maturity, the widespread operationalization of S-LCA remains limited. Key barriers include the complexity of the methodology, challenges in data collection and standardization, and the lack of institutional frameworks to support its integration into corporate decision-making (Waldekker and Molnar, 2014).

VI.1 Foundational Guidelines and Standards

The methodological foundations of S-LCA are primarily guided by two key references: the UNEP Guidelines for Social Life Cycle Assessment of Products (2009, updated in 2020), and the newly

published international standard ISO 14075 (2024). Together, these frameworks provide the conceptual structure, procedural steps, and recommended practices for conducting S-LCA studies in a systematic and credible manner. While the UNEP guidelines offer a flexible and developmental approach suited for varying levels of data availability and practitioner maturity, ISO 14075 aims to standardize the field and promote broader adoption by harmonizing terminology, structuring the assessment process (Dunuwila et al., 2025), and aligning S-LCA with other life cycle-based methods such as Environmental LCA (ISO 14040) and Life Cycle Costing (LCC).

VI.2 Phases and Structural Elements of S-LCA

The method is structured around four main phases (ISO 14075, 2024) similar to those outlined in ISO 14040 for the environmental LCA:

(1) Goal and Scope Definition, establishing the objectives of the study, the system boundaries, and the relevant stakeholder groups;

(2) Social Life Cycle Inventory (S-LCI), collecting social data associated with the processes and actors involved across the life cycle;

(3) Social Life Cycle Impact Assessment (S-LCIA), linking inventory data to potential social impacts using established indicators and frameworks; and

(4) Interpretation, analyzing the results to draw conclusions, identify critical issues, and propose recommendations, while considering data quality and uncertainties.

These phases mirror those of Environmental LCA (ISO 14040, 2006), but are adapted to address the qualitative and context-dependent nature of social data, often requiring stakeholder engagement, documentary analysis, and value-based assessments[5]. For instance, the S-LCI phase frequently involves the use of proxy data, expert judgment, or survey-based methods, particularly in cases where direct social metrics are unavailable or difficult to quantify (Bamana et al., 2021).

The goal and scope definition phase establishes the overall purpose of the study, the product system to be assessed, the geographical and temporal boundaries, and the stakeholders of interest. A critical component of this phase is the functional unit, which serves as a reference point for assessing and comparing social impacts across different systems. Unlike in environmental LCA, where the functional

[5] In the context of Social Life Cycle Assessment (S-LCA), a value-based indicator refers to an indicator that reflects ethical, cultural, or societal values rather than purely quantitative or physical measurements.

unit is often based on measurable quantities (e.g., “1 kg of packaging”), in S-LCA, the functional unit must also be meaningful from a social perspective, often requiring a combination of physical output and stakeholder relevance (Arcese et al., 2018).

The system boundaries define which life cycle stages and supply chain actors are included in the assessment, typically encompassing upstream (e.g., raw material extraction), core (e.g., manufacturing and transport), and downstream (e.g., use and disposal) activities. However, in S-LCA, the selection of system boundaries must also consider social relevance. This may involve including stakeholders or activities, such as subcontracted labor or informal waste collectors, that are often excluded in environmental LCA but are critical for capturing social risks and ethical concerns across the supply chain (Ayassamy and Pellerin, 2023).

VI.3 Impact Categorization and Interpretation in S-LCA

In terms of impact categories, the UNEP guidelines recommend organizing the assessment around stakeholder groups rather than environmental compartments or emission types. The six primary stakeholder groups include: workers, local communities, value chain actors, consumers, children, and society at large (UNEP, 2020). For each group, a series of subcategories or themes are defined, such as fair salary, occupational health and safety, access to material resources, and freedom of association. These subcategories form the basis for constructing impact pathways and selecting indicators for the assessment.

These impact pathways provide the conceptual link between inventory data and potential social outcomes, ensuring that each selected indicator is not only relevant to a stakeholder group but also meaningful in terms of its consequences (UNEP, 2020). For instance, in the case of the stakeholder group children, the absence of school enrollment data combined with reports of underage workers in upstream raw material extraction sites may form an impact pathway that points to child labor. This, in turn, is connected to broader social impacts such as restricted access to education, long-term poverty cycles, and violations of children's rights. By defining such pathways explicitly, S-LCA practitioners can enhance the transparency and interpretability of the assessment, ensuring that indicators are not used in isolation but reflect a deeper understanding of cause-and-effect relationships (Arcese et al., 2018). Moreover, impact pathways help in identifying social hotspots, areas in the supply chain where vulnerable populations, like children, are at elevated risk, thus enabling more focused mitigation strategies. This approach is useful in cases where direct standards may not exist, such as measuring community well-being or psychological safety. The careful construction of these pathways is therefore essential to translating qualitative and context-specific data into actionable insights aligned with the ethical objectives of social sustainability (Benoît et al., 2010).

In order to interpret social indicators in a structured and meaningful way, the 2020 UNEP Guidelines also introduce the concept of reference scales, which define how performance is evaluated relative to normative benchmarks or expected outcomes (UNEP, 2020). The reference scale approach compares observed practices to recognized standards—such as ILO conventions, national labor laws, or CSR frameworks—and classifies performance according to levels of compliance. This method is especially relevant for subcategories where clear normative expectations exist, such as minimum working age, fair wages, or the presence of health and safety protocols (Russo Garrido et al., 2018). The selection and application of an appropriate reference scale play a crucial role in shaping the ethical framing of S-LCA results. It ensures that assessments are not only evidence-based but also grounded in globally or locally accepted principles, thereby strengthening both the credibility and policy relevance of the analysis (Harmens et al., 2022).

VI.4 Types of Indicators

A distinguishing feature of S-LCA is its reliance on a range of indicator types suited to the qualitative and often non-numeric nature of social data. Indicators in S-LCA can generally be classified into three categories (UNEP, 2021):

- **Qualitative indicators,** which are descriptive in nature and derived from interviews, document analysis, field observations, or expert judgment. These are particularly useful when dealing with issues like human rights or worker satisfaction, where binary or scalar judgments are more appropriate than numerical data.
- **Semi-quantitative indicators,** which use ordinal scales or scoring systems (e.g., low–medium–high risk) to translate qualitative judgments into a structured format that can be aggregated or compared across systems. This category is often used for risk-based assessments or benchmarking purposes.
- **Quantitative indicators,** which provide measurable data (e.g., number of working hours, percentage of unionized workers, incidence rates of occupational injuries). These indicators are most often used when reliable statistical or administrative data are available and when social impacts can be meaningfully quantified.

The choice of indicators depends on the study's objectives, the availability and quality of data, and the contextual relevance to the stakeholder groups involved. Importantly, S-LCA does not mandate a universal set of indicators but encourages practitioners to adapt their selection based on local conditions, data accessibility, and stakeholder engagement.

VI.5 S-LCA Database: Comparison and Benchmarking

The quality and relevance of Social Life Cycle Assessment (S-LCA) results depend substantially on the database selected. Among the most established and academically referenced S-LCA databases are the Product Social Impact Life Cycle Assessment (PSILCA), the Social Hotspots Database (SHDB), and the SOCA . These three resources differ not only in structure and scope but also in their data modeling approaches and impact allocation methods.

PSILCA, developed by GreenDelta, is a tiered risk-based database designed to quantify social risks across life cycle stages. It supports two modeling approaches: one based on a worker-hour activity variable, which allocates risks proportionally to labor intensity, and another based on raw values, such as accident rates or wages, when such data are available. Impacts are linked to either the number of working hours or direct measured values, depending on the indicator and data availability. In the background, monetized economic flows (USD) are used for supply chain linkages. PSILCA includes over 15,000 processes covering a broad range of industries, commodities and countries (Maister et al., 2020). While it enables detailed modeling of social risks across supply chains, it relies on national or sectoral averages, which may limit its representativeness for specific companies, regions, or sites.

Similarly, the Social Hotspots Database (SHDB) also uses worker-hour-based modeling, built on the GTAP multiregional input-output framework. It maps social risks across over 140 countries and 57 industrial sectors, focusing on qualitative and semi-quantitative risk levels for themes like labor rights, human health, gender equity, and governance (Benoit-Norris et al., 2018). SHDB is especially useful in screening-level assessments for identifying potential social hotspots, although it does not provide detailed process-specific data. Like PSILCA, SHDB results are commonly tied to economic inputs (USD), making them suitable for top-down assessments.

In contrast, SOCA adopts a qualitatively different modeling principle. Rather than relying on aggregated sectoral risks, SOCA is directly linked to ecoinvent unit processes and expresses social impacts per physical reference flow (e.g., per kg of product, per unit of service). This allows for a more concrete linkage between specific process chains and their social implications (Hamed and Ciroth, 2024). Unlike the risk-based modeling in PSILCA and SHDB, SOCA evaluates the organizational capacity to manage social issues by drawing on qualitative data such as company practices, certifications, or stakeholder engagement mechanisms. While SOCA lacks the global sectoral breadth of the other two databases, it enables more granular, organization-specific assessments, especially relevant in site-focused or corporate-level S-LCA applications.

In sum, PSILCA and SHDB share a common structure in their use of worker-hours and economic modeling to allocate social risk, making them suited for upstream supply chain screening. SOCA, by

contrast, operates on a process-based model tied to physical product flows, offering a more grounded approach for case-specific organizational evaluations. The choice between these tools should be guided by the intended scale, resolution, and stakeholder focus of the S-LCA study.

VI.6 Application of S-LCA to Procurement Contexts

Relevance for supply chain assessment

S-LCA plays a crucial role in evaluating the social dimension of sustainability within global supply chains. As procurement systems grow more complex and geographically dispersed, organizations are increasingly encouraged to assess not only environmental and economic impacts but also the social implications of sourcing decisions (European Commission, 2019a). S-LCA provides a structured methodology to evaluate such impacts across the life cycle of products and services, enabling companies to identify social risks, inequalities, and value creation opportunities among supply chain actors (Norris et al., 2014)

One of the core strengths of S-LCA lies in its ability to highlight social hotspots of specific locations or processes within a supply chain where negative social conditions such as forced labor, poor working conditions, or lack of access to education are most likely to occur. This makes it particularly relevant in procurement contexts where supplier tiers are difficult to trace and where reputational and operational risks are significant (Feschet et al., 2010). The UNEP guidelines and ISO 14075 emphasize that S-LCA must be grounded in transparency, stakeholder participation, and contextual interpretation, in order to reflect the complexity and variability of real-world procurement environments (ISO 14075, 2024; UNEP, 2020). These principles help address the ethical subjectivity inherent in social sustainability and distinguish S-LCA from more narrowly quantitative approaches, such as traditional environmental LCA or supply chain audits.

Strategic Integration of S-LCA in Procurement

S-LCA has been applied in a variety of sectors where supply chain complexity and social risks are significant. These include construction (Dong and Ng, 2015), agriculture (Feschet et al., 2010), textiles and garments (Iofrida et al., 2024), electronics (Ghisellini et al., 2023), automotive (Karlewski et al., 2019), and packaging (Yıldız-Geyhan et al., 2019). The diversity of applications illustrates the broad relevance of S-LCA and its potential to support socially responsible decision-making across procurement-intensive industries.

Building on this breadth of application, the integration of S-LCA into procurement processes presents clear strategic value. It enables organizations to move beyond compliance-driven approaches and toward more proactive identification and mitigation of social risks, particularly in lower-tier suppliers

where monitoring is limited. When embedded within procurement workflows, S-LCA supports alignment with leading frameworks such as the Guiding Principles on Business and Human Rights (UN, 2011), by enabling companies to identify, assess, and address adverse human rights impacts across their supply chains in a structured and evidence-based manner.

Moreover, the use of dedicated S-LCA tools such as the Social Footprint method enables firms to conduct risk-informed supplier selection, reinforce contractual requirements, and track social performance across the supply chain (McElroy, 2015). As a context-based approach, this method evaluates an organization's social sustainability performance relative to normative thresholds in vital capitals, such as human, social, and constructed capital, offering a structured framework for assessing whether operations contribute positively to stakeholder well-being.

The growing importance of S-LCA in procurement is further reinforced by the guidance of both the UNEP guidelines and ISO 14075, which emphasize the role of transparency, stakeholder participation, and contextual interpretation. These principles are essential for navigating the normative complexity of social sustainability and mark a departure from more data-intensive, yet socially limited, approaches (ISO 14075, 2024; UNEP, 2020). As implementation challenges persist, particularly regarding data availability and methodological consistency, there is a parallel emergence of enabling infrastructures. These include robust databases, harmonized indicator libraries, and digital platforms designed to facilitate the operationalization of S-LCA in both business and policy contexts. Such developments are particularly urgent in sectors where social risks are high but traceable data remains limited. They underscore the need for continued methodological refinement to ensure that S-LCA becomes a practical and impactful tool for real-world procurement decision-making (European Commission, 2019a).

VI.7 Challenges and Limitations in Practice

Despite the increasing methodological development of S-LCA, its practical implementation remains constrained by persistent challenges. These include limited data availability and quality, inconsistent stakeholder engagement, and difficulties integrating S-LCA into existing managerial and accounting systems (Pollok et al., 2021).

A major limitation in operationalizing S-LCA is the difficulty of obtaining reliable, disaggregated, and context-specific social data across complex supply chains (Huang et al., 2025). While environmental accounting has advanced significantly in recent decades, particularly with the widespread availability of tools and databases for assessing greenhouse gas emissions, social data remains fragmented, qualitative, and often unavailable at the site or supplier level (Abubakr et al., 2024).

Moreover, new regulatory developments are accelerating the urgency to address integration barriers between sustainability data and conventional management systems. This challenge is becoming increasingly pressing with the introduction of emerging frameworks such as the Digital Product Passport in Europe (expected by 2027), which will require companies to disclose detailed product-level information on supply chains, recycling content, and polluting substances. These disclosures are expected to cover not only environmental impacts but also human and social rights concerns arising from companies' operations and from the products themselves (European Commission, 2024). This raises important questions about how to systematically integrate social impacts into product-level assessments and embed them into traditional management and cost accounting practices (Bonilla-Alicea and Fu, 2021).

At the same time, companies increasingly concerned with the time and effort required to collect and integrate social impact data into their internal information systems (Ramos Huarachi et al., 2020). The proposed framework, in Chapter 5, may offer significant advantages in this regard: the costing model used (i.e., Time-Driven Activity-Based Costing) draws on data already embedded in enterprise systems, reducing the data burden and facilitating integration into existing managerial processes (Kaplan and Anderson, 2007). This suggests that the pathway forward may depend on combining social impact metrics with cost-based data systems already in use, such as Activity-Based Costing models.

VI.8 Embedding Social Life Cycle Assessment into Organizational Decision-Making Frameworks

The practical limitations discussed in the previous section highlight the need for S-LCA to evolve beyond a diagnostic tool toward one that is structurally embedded in business systems. To achieve this, its integration with accounting models becomes both a methodological and strategic imperative (Turzo et al., 2024). Procurement decisions are inherently monetary, and sustainability considerations must therefore be translated into formats compatible with internal financial and managerial systems (Naro and Rambaud, 2023). Aligning S-LCA with monetary models offers a pathway for doing so, linking social impact data with value creation and monetary structures in a way that can inform real-time decisions.

Despite its conceptual maturity, S-LCA still faces several challenges regarding its operationalization. These include limited access to primary data (Bouillass et al., 2021) and poor integration with business decision-making tools (Jørgensen et al., 2008). Although S-LCA can highlight social hotspots, it lacks mechanisms to allocate these impacts in ways that reflect company-specific structures or internal cost flows.

Recently, studies have emerged seeking to complement S-LCA with Life Cycle Costing (LCC) to address these limitations (Ostojic and Traverso, 2024; Rahman et al., 2025; Webb et al., 2025). However, LCC

often operates independently of managerial accounting systems and is typically used as an external environmental valuation tool, limiting its relevance for internal decision-making.

Although both approaches are life cycle-based, their integration faces several persistent barriers (Larsen et al., 2022; Sala et al., 2015; Waldekker and Molnar, 2014). First, the heterogeneity in data formats makes it difficult to combine them within a unified operational model. Second, data collection for social impacts and LCC often requires significant time and effort, relying on generic databases that do not reflect company-specific operations, thereby limiting both accuracy and applicability. Third, existing tools rarely leverage internal accounting systems or enterprise software (e.g., ERP), limiting their applicability for managers who require real-time, activity-based insights for operational decisions. As a result, current models for integrating S-LCA and LCC remain largely conceptual and have yet to deliver practical, operational solutions for corporate use (Pérez-López et al., 2025).

These challenges reinforce the rationale for developing integrated models that bridge social performance metrics with enterprise-level accounting systems.

VII. Activity-Based Costing (ABC) and Time-Driven Activity-Based Costing (TD-ABC)

Activity-Based Costing (ABC) emerged in the 1980s as a method to improve the accuracy of overhead allocation by assigning indirect costs to activities based on their actual consumption of resources (Cooper and Kaplan, 1988). It represented a shift from traditional costing methods, which relied on broad averages and often distorted cost visibility, particularly in complex organizations. ABC provided a more granular view of cost structures, helping firms trace operational costs to specific tasks or processes (Kenton, 2024). However, it soon became apparent that implementing and maintaining ABC systems required extensive data collection, detailed activity mapping, and subjective estimates from employees, all of which limited its scalability and practical usefulness over time.

To address these limitations, Kaplan & Anderson (2007) introduced Time-Driven Activity-Based Costing (TD-ABC), a simplified and more scalable version of ABC that uses time as the core cost driver.

TD-ABC is an advanced costing methodology to address the limitations of traditional Activity-Based Costing (ABC). Unlike ABC, which often requires time consuming data collection and subjective employee declarations about their activities, TD-ABC streamlines the cost allocation process by using time estimates as the primary cost driver (Hoozze and Hansen, 2014). It calculates the cost of activities based on an estimation of the time required to perform them, using time equations to estimate additional time and resources consumption, allowing for more efficient cost assessment and identification of gaps between available and used resources (Demeere et al., 2009). This enables decision-makers to reallocate resources to new products more effectively or optimize resources use.

TD-ABC has gained traction, particularly in services sectors like healthcare or banking, where it helps organizations understand the use of resources at the activity-level (Siguenza-guzman et al., 2013). By leveraging internal information systems, such as Enterprise Resource Planning (ERP) software which integrates key business functions like finance, procurement, and operations, TD-ABC supports more agile and informed managerial decision-making.

Despite its managerial strengths and operational relevance, TD-ABC has historically overlooked sustainability indicators. While some efforts have been made to integrate environmental concerns through frameworks like E-ABC (Antić et al., 2021) or ABC-LCA (Jourdaine et al., 2021), social dimensions remain largely absent. This is partly due to the lack of documentation on the origin and nature of resources, even though it is well established that resource provenance can be associated with significant disparities in labor conditions and social rights (Ortiz-Cea et al., 2025). This highlights a critical gap for companies aiming to combine internal cost tracking with structured, data-compatible social impact assessment.

This potential is further amplified when TD-ABC is embedded within digital infrastructures. As organizations increasingly adopt automated systems and intelligent tools to manage environmental and social data at scale, the integration of costing models with digital platforms becomes essential.

VIII. Digitalization, Automation, and Intelligent Systems in Environmental Assessment

As environmental and social assessments become central to corporate sustainability, regulatory compliance, and supply chain transparency, traditional life cycle methodologies face new challenges in scale, speed, data integration, and reproducibility. The complexity and volume of required data, especially in Scope 3 emissions accounting, demand the support of digital infrastructures, automation frameworks, and intelligent systems. Tools such as Artificial Intelligence (AI), Natural Language Processing (NLP), Product Data Management (PDM), Enterprise Resource Planning (ERP), automated APIs, data visualization platforms, and emerging technologies like blockchain now play a growing role in enabling scalable, transparent, and repeatable sustainability assessments.

VIII.1 Automating Environmental Assessment: Challenges and Opportunities

Environmental Assessment workflows are typically manual and expert-driven, requiring significant time and technical resources to compile foreground and background data, build models, and interpret results (Smaldone et al., 2025). This approach poses serious limitations in contexts where rapid, frequent, or portfolio-wide assessments are needed, such as in procurement, carbon disclosure reporting, or product design optimization (Wohlschlager et al., 2023). Many organizations manage thousands of suppliers and product configurations, making it impractical to apply traditional methods at this scale (Borschewski et al., 2024). Furthermore, manual workflows are prone to inconsistencies,

hidden assumptions, and limited traceability, which hinder reproducibility and transparency (Heijungs and Suh, 2002).

Automation and digitalization are therefore key enablers for scaling environmental assessment (Klymenko et al., 2021). By embedding life cycle thinking into enterprise systems and digital platforms, environmental metrics can be systematically computed, tracked, and integrated into day-to-day decision-making processes (Lo-Iacono-Ferreira et al., 2017). This transformation involves not only new software tools but also restructured data pipelines, standardized modeling interfaces, and computational frameworks capable of handling big data and multi-level analysis (Schneider et al., 2023).

VIII.2 Intelligent Systems and Digital Infrastructure for Sustainable Procurement

The expansion of environmental assessments from isolated case studies to full organizational and supply chain coverage requires the integration of life cycle thinking into enterprise-wide digital systems (Köck et al., 2023). A critical enabler of this integration is the development of digital infrastructure that allows environmental data to be linked, automated, and analyzed alongside core business operations (Rodrigues, 2024). Several key components support this transformation, including Enterprise Resource Planning (ERP) systems, Product Data Management (PDM) platforms, Application Programming Interfaces (APIs), and business intelligence tools.

ERP systems, such as SAP, Oracle, or Microsoft Dynamics, are central management platforms that coordinate financial, logistical, and operational data across organizations. These systems track procurement transactions, production quantities, energy consumption, and transportation; crucial parameters for sustainability assessments (Alzahmi et al., 2025; Anaya et al., 2025). When connected to environmental databases or life cycle modeling tools via Application Programming Interfaces (APIs), ERP systems enable automated calculation of environmental indicators such as greenhouse gas emissions flows (El Haouat et al., 2023). For example, purchased goods and services can be mapped to environmentally extended input-output (EEIO) coefficients, enabling continuous Scope 3 emissions accounting based on real-time expenditure data.

PDM systems store detailed information about the technical attributes, material composition, and assembly processes of individual products. These data structures are essential for LCA at the product level (Tao and Yu, 2018). When connected with LCA software, PDM systems allow automatic generation of impact assessments based on bill-of-materials, component hierarchies, and product configurations (Ciroth et al., 2013). This digital link facilitates rapid screening, design optimization, and supplier-specific impact modeling (Jakobsen and Tambo, 2025).

Business intelligence tools, such as Power BI, Tableau, or Looker, support the interpretation and communication of environmental data through dynamic dashboards and visual reports. These tools are increasingly used to monitor key environmental performance indicators, compare supplier footprints, identify hotspots, and inform decision-making across procurement, design, and compliance teams (Shaikh, 2024). By integrating environmental assessment outputs into business dashboards, environmental information becomes accessible to non-specialists and can be embedded into strategic planning and operational reviews.

In addition to supporting internal analytics, these digital systems also enable organizations to participate in emerging international transparency frameworks such as PACT (WBCSD, 2023a). To contribute to PACT, companies must generate high-quality emissions data often derived from ERP, PDM, and LCA systems, and share it securely with supply chain partners through digital interfaces and common data formats. By enabling traceable, comparable, and verifiable environmental data exchange, PACT fosters cross-sector collaboration on Scope 3 emissions reductions and enhances the accountability of corporate climate strategies (Alzahmi et al., 2025). ERP systems, LCA software, and API-based platforms thus form the technical backbone of a new generation of digitally enabled, procurement-centered environmental accounting aligned with global transparency initiatives (Rodrigues, 2024).

VIII.3 Overcoming Language and Data Format Barriers in Environmental Modeling

Artificial Intelligence (AI) refers to the field of computer science focused on creating systems that can perform tasks typically requiring human intelligence, such as learning, reasoning, decision-making, and pattern recognition (Glover, 2025). Within this broad domain, Natural Language Processing (NLP) is a specialized area that enables computers to understand, interpret, and generate human language. NLP combines techniques from linguistics, machine learning, and computational modeling to process and extract meaning from large volumes of textual data (Ayadi et al., 2020).

These technologies are opening new possibilities for automating environmental data extraction and interpretation. Many relevant data sources, such as supplier questionnaires, product specifications, or EPDs, are stored in unstructured or semi-structured textual formats. NLP tools can parse these documents, extract relevant parameters (e.g., global warming potential, system boundaries, material content), and convert them into structured data suitable for integration into LCA models (Blanchy et al., 2023). By doing so, AI-powered systems reduce the need for manual data entry and interpretation, while enabling faster and more consistent data processing across diverse formats and languages (Lee, 2025).

Multilingualism is another significant challenge in global supply chains. Translation systems like MarianMT, an open-source neural machine translation model, offer the ability to automatically translate technical environmental documentation, supplier responses, or EPDs from one language to another (Lohar et al., 2023; Zappatore and Ruggieri, 2024). This enables organizations to work across linguistic boundaries, harmonize data, and expand the usability of international environmental databases such as INIES or ECO Platform.

Beyond basic language processing, more advanced applications of AI in environmental assessment involve semantic modeling and the use of vector embeddings to align heterogeneous data sources, using BERT model (Li et al., 2024). In this context, vector embeddings refer to mathematical representations of words, phrases, or entire documents in a multi-dimensional numerical space, where the proximity of two vectors reflects the semantic similarity of their content (Reimers and Gurevych, 2019). These representations are generated by machine learning BERT models trained on large collection of data and are capable of capturing nuanced relationships between terms that traditional keyword-based methods often miss (Devlin et al., 2019; Mikolov et al., 2013).

Applied to environmental data integration, these techniques allow procurement records, supplier descriptions, or product names, often recorded inconsistently across systems, to be matched with appropriate emission factors or LCI datasets, even when naming conventions, languages, or sector classifications differ (Reimers and Gurevych, 2019; Zhong et al., 2024). For example, the same material might be labeled “cast iron pipe” in one supplier catalog, “ferrous piping” in another, and “ductile iron component” in a third. Embedding-based matching systems can recognize that these terms are semantically equivalent or closely related and align them with a unified category in an EEIO model or an LCA database.

This capability is particularly valuable in the context of automated Scope 3 emissions estimation, where organizations must link thousands of procurement line items to environmental coefficients (Tamym et al., 2023). Manual mapping is time-consuming, error-prone, and often unscalable. AI-enabled semantic matching allows for automated and more accurate classification of goods and services into standardized categories, thereby streamlining the assignment of emissions factors and improving consistency across datasets.

Furthermore, Large Language Models (LLMs), such as GPT-based architectures, extend these capabilities by enabling more complex reasoning and contextual understanding. LLMs can assist in interpreting supplier documentation, validating methodological assumptions, or generating structured summaries of environmental disclosures (Trébucq and Valakhanovich, 2025). They can also be employed to automatically draft supporting documentation for audits or compliance, conduct

terminology harmonization across datasets, or suggest corrections when data inconsistencies arise. In methodological development, LLMs can serve as intelligent assistants, offering expert support in the construction of hybrid models or the selection of appropriate impact categories (Sinha, 2025).

In parallel, Machine Learning (ML) techniques are increasingly applied to detect complex behavioral patterns in firms. For instance, Veganzones and Séverin (2025) demonstrate how ML can reveal latent financial risk profiles associated with earnings manipulation. While their study is not focused on sustainability, it illustrates the broader potential of ML to detect non-obvious patterns in corporate data, a capacity that could be valuable in anticipating sustainability-related governance risks or inconsistencies across environmental or social datasets. Such tools may inspire future developments in AI-driven sustainability assurance.

Together, these capabilities support a more automated, scalable, and intelligent approach to environmental modeling, one that is essential for operationalizing Scope 3 accounting, supporting procurement decisions, and ensuring consistency across global, multi-lingual supply chains.

VIII.4 Blockchain for Data Integrity and Traceability

Blockchain technology offers promising avenues for securing environmental data and ensuring traceability across complex and decentralized supply chains. By storing environmental declarations, carbon intensity data, or recycled content percentages on immutable ledgers, blockchain can increase transparency and reduce the risk of greenwashing or data manipulation (Varma et al., 2024). Smart contracts, which execute automatically when predefined conditions are met, can enforce compliance with sustainability requirements in procurement or supply chain agreements (Wang et al., 2019).

For instance, a supplier's verified EPD or carbon intensity record could be cryptographically recorded and accessed by downstream buyers, auditors, or regulators. This application is particularly relevant for chain-of-custody certifications, ESG audits, or carbon credit tracking, where assurance and traceability are essential. Although blockchain adoption in environmental accounting remains nascent, pilot projects in sectors like fashion, agriculture, and electronics suggest increasing viability and interest (Saberi et al., 2019).

Tokenization of environmental impacts, such as carbon offsets, water rights, or biodiversity credits, is another emerging application. These tokens can be traded or assigned to specific products, allowing digital tracking of environmental attributes and facilitating market-based incentives for low-impact production. However, methodological and governance questions remain open, particularly regarding the alignment of blockchain-based systems with standardized LCA and GHG accounting frameworks (Vladucu et al., 2024).

VIII.5 Reproducibility and Automation in Portfolio-Scale Assessment

One of the major advantages of digitalization is the increased reproducibility of environmental assessments. Automated data pipelines, standardized model templates, and version-controlled databases reduce the subjectivity and inconsistency often associated with manual LCA modeling (Uhlhorn et al., 2024). This is particularly important for comparative assessments, regulatory disclosures, and third-party verification.

In large organizations, the ability to assess entire product portfolios or supplier ecosystems hinges on scalable and automated workflows. Digital twins of products or operations, continuously updated via ERP and PDM systems, can serve as the foundation for real-time environmental monitoring (Alzahmi et al., 2025). Similarly, automated Scope 3 accounting platforms can integrate spend data, physical inventories, and LCI databases to produce up-to-date emissions profiles that adapt to purchasing behavior and market fluctuations (Northmore and Hudson, 2022).

Cloud computing infrastructure supports these capabilities by enabling parallel processing, high-frequency updates, and integration with data science tools. Combined with visualization platforms and stakeholder dashboards, this creates an “environmental control tower” for organizations, offering continuous insight into hotspots, risks, and opportunities for decarbonization and sustainability improvement (Biswas et al., 2024; Tripathi et al., 2024).

B. Review of Scope 3 Accounting Practices in Academic Literature

This section provides a comprehensive review of current practices for accounting Scope 3 emissions in organizational procurement, with a focus on carbon accounting methodologies used in academic case studies. It examines the strengths and limitations of Life Cycle Assessment (LCA), Environmentally Extended Input-Output (EEIO) analysis, and hybrid methods, while also analyzing standards, data sources, and system boundaries. Special attention is given to how these methods align with corporate sustainability goals, regulatory expectations, and practical decision-making.

A summary version of this analysis has been accepted for publication as a book chapter in the LCM 2025 Proceedings (Springer), titled «Sustainable Innovation or Merely Reporting? State of The Art of Assessing Scope 3 Emissions of Organizational Procurement » (Essouid et al.)

I. Introduction

Today, organizations face growing pressure to mitigate their environmental impacts, particularly their carbon footprint. This includes not only direct GHG emissions from their operations but also a wide variety of indirect activities across their supply chains, referred to as Scope 3 carbon emissions. These emissions encompass upstream activities, including the extraction of acquired raw materials, along with downstream activities such as product usage and disposal (WRI and WBCSD, 2011a). Even though organizations do not have direct control over these external activities, they can influence them by embracing sustainable procurement practices or applying environmentally friendly design concepts (Vieira et al., 2024). Current standards and initiatives, such as the GHG Protocol and the Science Based Targets initiative (SBTi), are planning to adopt revised methods to better address these emissions, which often make up a significant portion of a company's carbon footprint. Research shows that over 75% of emissions in many sectors come from Scope 3, mainly from purchased goods and services (Alvarez et al., 2014; Blanco et al., 2016; Kjaer et al., 2015; Rossi, 2007). Furthermore, trends in manufacturing, such as increasing complexity in supply chains, have shifted substantial environmental burdens onto suppliers, which complicates an organization’s understanding of its indirect activities and emissions. As a result, it is critical for businesses to accurately measure their Scope 3 carbon emissions to gain knowledge about the corresponding emission sources and to identify impactful reduction strategies.

Recent regulations, like the European Union's Corporate Sustainability Reporting Directive (CSRD), highlight the necessity for increased standardized and concise reporting on environmental impacts (European Commission, 2023a). The CSRD mandates large companies and listed SMEs in the EU to provide specific details about their sustainability initiatives, including reporting on their Scope 3 carbon

emissions. This guideline is in line with the EU's wider objectives outlined in the European Green Deal (European Commission, 2019b), which seek to hold companies responsible for their complete environmental and social impact, promoting sustainable practices across the value chain. Complementary legislative efforts, such as the EU Green Claims Directive (European Commission, 2023b) and the Omnibus Directive (European Commission, 2025b), further reinforce the demand for verifiable, science-based sustainability disclosures. The Green Claims Directive aims to combat greenwashing by requiring companies to substantiate voluntary environmental claims with rigorous evidence and third-party verification. Meanwhile, the Omnibus Directive introduces simplification measures to reduce reporting burdens while maintaining core transparency requirements.

In addition, the Ecodesign for Sustainable Products Regulation (ESPR) expands sustainability requirements beyond disclosure by establishing mandatory product design criteria related to durability, reparability, and resource efficiency. As a cornerstone of the EU's Circular Economy Action Plan, ESPR compels companies to embed environmental considerations directly into product development and procurement, making sustainability a performance requirement, not just a reporting obligation (European Commission, 2024). A key operational mechanism under ESPR is the introduction of the Digital Product Passport (DPP), which will digitally record and communicate essential information on a product's environmental footprint, material composition, reparability, and recyclability (European Commission, 2024). The DPP aims to support informed purchasing, sustainable design, and end-of-life decision-making by ensuring traceability and transparency across supply chains.

The CSRD's implementation is expected to encourage companies to enhance the precision and accountability of their emissions data through stakeholder pressure from customers, financial institutions, and the public. While increased transparency is welcomed, the assessment of carbon emissions must go beyond reporting obligations or carbon offsetting to actual sustainable innovation practices and decarbonization strategies (Baehr et al., 2024).

Based on the overview provided in Section 2.A, Scope 3 accounting employs two approaches: Life Cycle Assessment (LCA) and spend-based accounting (Finogenova et al., 2019). LCA offers a thorough analysis of environmental impacts at the product or process level, enabling a detailed analysis of hotspots as a basis for strategic decisions towards decarbonization strategies. Especially supplier-specific LCA data can help organizations understand and manage emissions in the supply chain. However, LCA methods are frequently limited by data gaps, data quality, as well as time and resource-intensive applications. Required LCA-model cut-offs, where processes outside of the assessment's system boundaries are excluded, additionally result in underestimation of emissions due to truncation errors while the incorrect handling of system boundaries can lead to double counting (Finogenova et

al., 2019; ISO 14040, 2006). To overcome some of these limitations, the Organizational Life Cycle Assessment (OLCA) framework has been developed to extend the principles of LCA to the organizational level, enabling more comprehensive evaluations of Scope 3 emissions across procurement portfolios.

Conversely, spend-based accounting uses EEIO to calculate emissions according to financial spending. Although this method provides extensive coverage, it often lacks the precision needed to accurately measure emissions for individual products, potentially resulting in overestimated figures (Suh, 2009; Wiedmann et al., 2009). For example, according to recent industry feedback, methods that calculate carbon emissions based on spending can exaggerate emissions for certain industries when compared to methods based on LCA (Aigner, 2024). Additionally, spend-based approaches do not enable tracking of the emissions to their source. Nevertheless, these methods remain widely used due to their ease of implementation and cost-effectiveness, particularly in situations with limited access to high-quality data for complex and dynamic supply chains, where the variability in supplier relationships complicates stable boundary definitions (Vieira et al., 2024). Furthermore, applications such as sustainability reporting and voluntary carbon compensation do not require the use of more precise methodologies, likely hindering the implementation and development of more robust methodologies.

Hybrid models that combine LCA with spend-based data or integrate physical data at varying resolutions hold promise for addressing challenges related to data availability and quality, thereby facilitating comprehensive assessments at the organizational level. At the same time, described methodological compromises in hybrid models persist (Finogenova et al., 2019). If left unattended, these compromises could hinder organization's abilities to foster sustainable innovation effectively, impede efforts to reduce carbon emissions in supply chains, and to develop harmonized, transparent Scope 3 calculations. Recent surveys, such as those conducted by SBTi, show that depending on the sectors 40-80% of companies still rely on monetary data for emission calculations, while only 6% utilize supplier-specific data, highlighting that Scope 3 accounting remains underdeveloped in many organizations (SBTi, 2024a). Especially Procurement emissions, given their significance and the limited insight available to the assessing organization, necessitate the use of robust calculation methodologies.

The heterogeneous methods employed lead to inconsistencies, inaccuracy, and a lack of comparability. To clarify methodological choices for the calculation of upstream Scope 3 carbon emissions and to develop effective sustainable innovation and decarbonization strategies, a detailed overview of common approaches is necessary. This study examines different methodologies for emission assessments based on the example of organizational procurement emissions and aims to help

organizations establish reliable climate mitigation strategies and to choose appropriate methods to fulfill their assessment objectives. Furthermore, we want to inform relevant stakeholders about identified benefits and challenges, supporting the discussion about further developments and the harmonization of methods by addressing the following questions:

1. Which carbon accounting methodologies and practices for the calculation of procurement emissions are employed in academic literature, and which strengths and challenges can be identified?
2. What inconsistencies across standards, methodologies, and case studies in the calculation of procurement emissions can be observed in academic literature, and what pathways can be proposed to harmonize these approaches for improving Scope 3 accounting practices?
3. How suitable are the employed methods to fulfill the sustainability goals set in the selected case studies?

To answer these research questions, a systematic literature review following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology (Page et al., 2021) was conducted. The review focuses on scientific case studies that assess procurement-related Scope 3 emissions and the methodologies they employed. This section is structured to first describe the methodology used to select relevant case studies on procurement-related emissions (II). It then presents the results of the literature analysis (III), focusing on the methodological approaches identified in the selected cases, including applicable standards, calculation methods, data sources, defined objectives, and the strengths and challenges of each approach. Building on this, the section discusses key gaps, inconsistencies, and assesses the suitability of existing practices for informing effective climate mitigation strategies (IV). Finally, it concludes with a synthesis of key insights and outlines areas for future research (V).

II. Method

Following the PRISMA framework, this review adheres to the seven-stage process for systematically identifying, evaluating, and including relevant studies. The PRISMA methodology enables replicability through a transparent and reliable review process (Page et al., 2021). The full PRISMA checklist is available in the Appendix 2-1 (A1). Figure 2-13 illustrates the screening process.

In **Step 1**, a search for research articles published prior to May 2024 using Web of Science (WOS) and Scopus databases using various combinations of keywords, their abbreviations and synonyms, including *organizational life cycle assessment, environmentally extended input-output, carbon accounting, Scope 3, procurement, and supply chain* was conducted. Only peer-reviewed articles written in English and available in these databases before the access date were included. While the

literature review requires a finite time frame, there is a potential limitation of excluding studies published after step 1 was completed in May 2024.

Step 2 was to eliminate duplicate studies and non-peer-reviewed papers. Despite the language filter applied in Step 1, some non-English articles were still identified in this step and subsequently excluded.

Step 3 involved rapid screening by reading titles, abstracts, and keywords to exclude articles that were not relevant to carbon accounting practices and procurement within the context of goods and services, including review papers. Articles that failed to demonstrate relevance to either field were excluded.

Steps 4 and **5** involved a full text screening of articles that had passed the first two phases. Articles that failed to directly address carbon accounting practices and procurement at the organizational level (country, product, process) were excluded. Additionally, studies were removed if their text was not explicit enough for the reviewers to determine how methods were applied and what the assessment entailed.

For **Step 6**, to broaden the research scope, additional relevant articles were identified by checking the citation of key articles found in Step 5 using Google Scholar.

Step 7 involved a structured three-level evaluation of the final pool of studies. An examination through the lenses of both carbon accounting and procurement at organizational level was conducted as a comprehensive assessment of the selected studies. First, an overview of carbon accounting research trends was conducted by identifying key journals, year trends, geographical distribution, and sectoral focus, providing insights into the evolution of carbon accounting in procurement research. Second, the methodologies used in the selected studies were examined, distinguishing between Life Cycle Assessment (LCA), Environmentally Extended Input-Output (EEIO) analysis, and hybrid methods integrating monetary-based approaches and LCA, allowing for the identification of key methodological gaps and strengths in assessing carbon emissions from organizational procurement. Finally, case studies were evaluated using the LCA framework by analyzing key steps, starting with goal and scope definition, followed by inventory analysis and impact assessment methods, ensuring a structured comparison of how carbon accounting practices are applied in real-world procurement contexts.

Beyond identifying relevant papers, this structured review process (detailed in the Appendix 2-1 (A2)) ensures consistency in how studies are compared and synthesizes key methodological elements. The detailed search strategy and screening process, as well as the list of complete search results, are depicted in the review matrix (detailed in the Appendix 2-1 (A5)). In total, 384 search results with 9 additional articles were analyzed and 44 articles with over 54 case studies were included in this review.

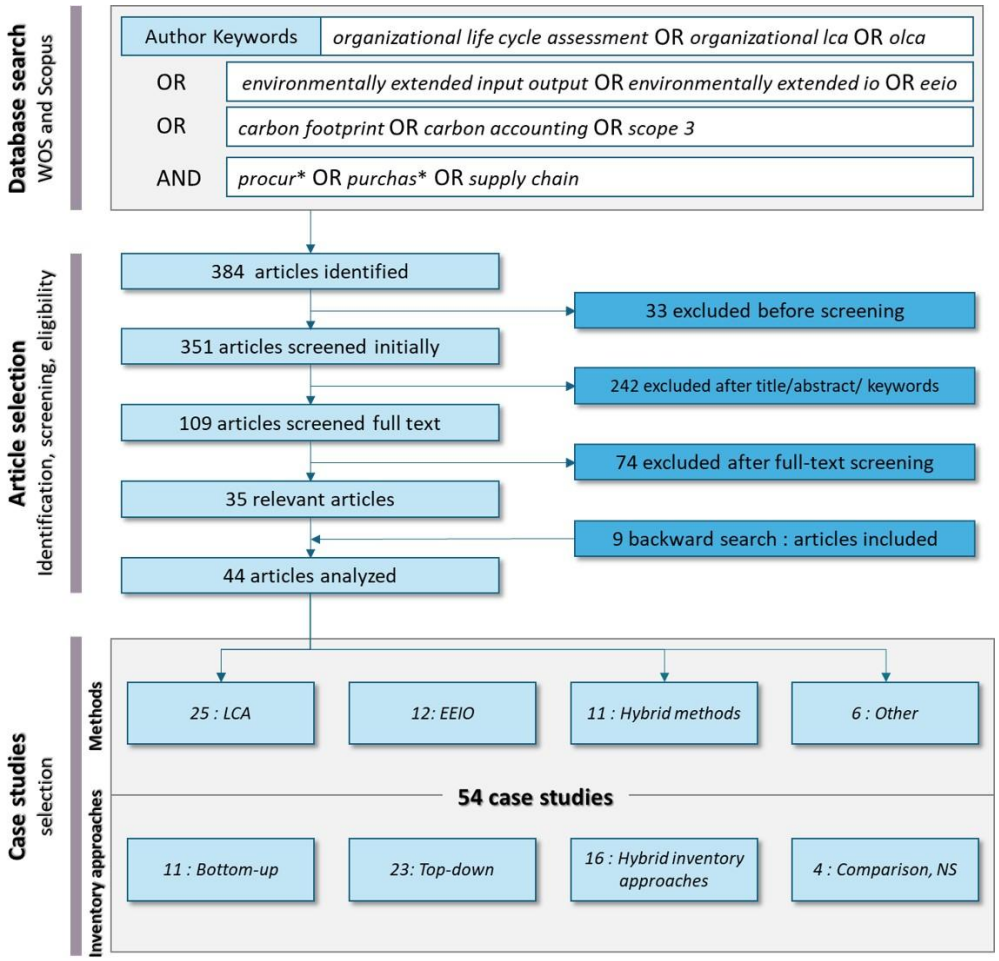


Figure 2-13 Literature Research and Review Methodology

III. Results

This section presents findings from the selected case studies on carbon accounting in organizational procurement. It examines key methodological choices, including system boundaries, data collection approaches, and quantification methods.

III.1 Overview of Research on Carbon Accounting of Organizational Procurement

To provide a broader perspective, this section highlights the most relevant academic journals, examines temporal trends in the field, and identifies key industrial sectors contributing to research on carbon accounting in organizational procurement.

III.1.1 Key Journals and Temporal Trends

First, we identified the most relevant journals regarding research on carbon accounting and procurement practices at the organizational level. Figure 2-14 highlights that the *'Journal of Cleaner Production*' topped the list with 12 articles, followed by the '*International Journal of Life Cycle Assessment'* with 6 and the '*Journal of Industrial Ecology*' with 4. Articles in these journals represent the major peer-reviewed avenues related to methodologies for carbon accounting in organizational

procurement processes. This distribution highlights the significant contribution of these journals in advancing research at the intersection of sustainability, LCA, and procurement strategies.

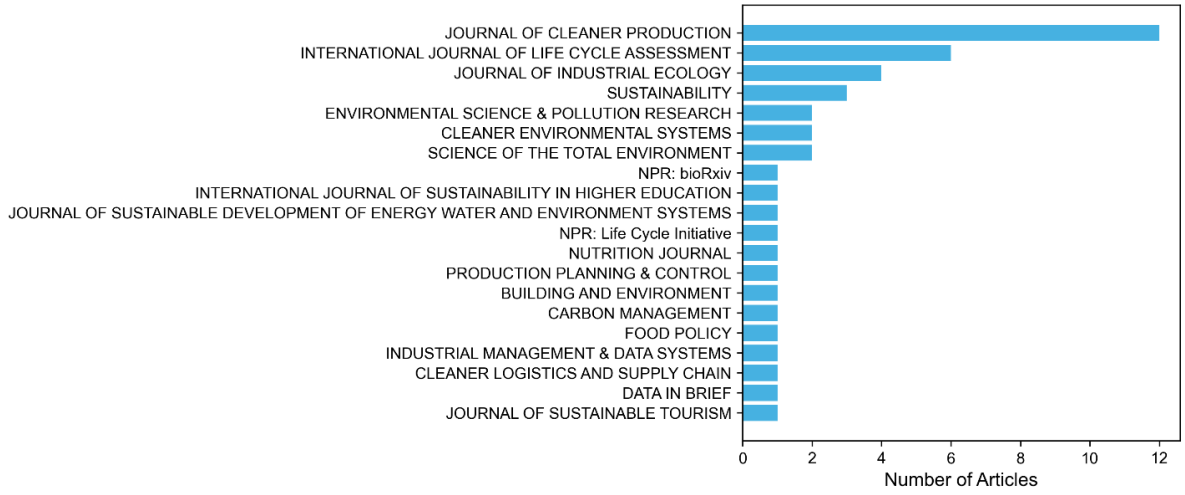


Figure 2-14 Number of Articles Published by Journal

In addition to identifying the leading journals, we also examined how the research has evolved over time. As shown in Figure 2-15, the number of articles published on this topic has fluctuated, with significant spikes in 2015-2016 and 2022-2023. The first spike corresponds to the adoption of the Paris Agreement and the following wave of sustainability initiatives that drove carbon accountability research across industries. The year 2023 spike with 9 articles is explicable due to the increased global focus on carbon accounting, driven by the rise of Net-Zero targets, heightened attention to Environmental, Social and Governance (ESG) factors, the impact of the COVID-19 pandemic on supply chain sustainability, and the introduction of stricter environmental regulations such as the European Green Deal. Likely, these factors have intensified academic interest in carbon accounting practices at the organizational level.

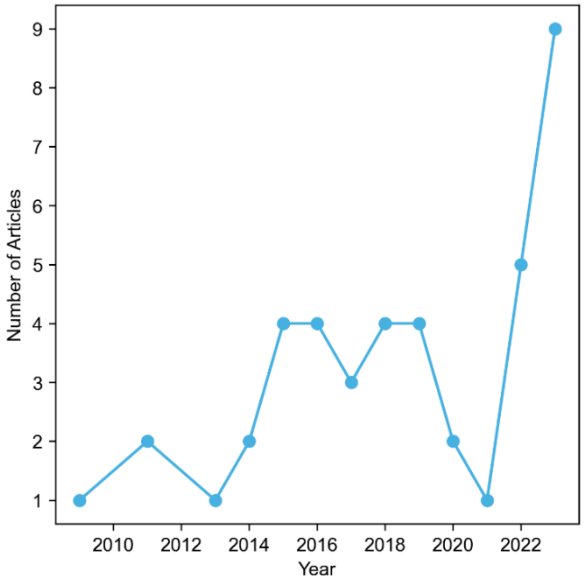


Figure 2-15 Number of Articles Published Over Time

III.1.2 Sectoral and Geographical Distribution

The sectoral distribution of the reviewed case studies, as classified by NACE sector codes lifts the veil on a clear emphasis on the *'Manufacturing'* sector, accounting for 20 articles. This prominence is notable considering the manufacturing sector's immense contribution to global carbon emissions and its complex supply chains, particularly in sectors such as food and beverage manufacturing (Montoya-Torres et al., 2015; Pelton and Smith, 2015) and the automobile industry (Finogenova et al., 2019; Lee, 2011). The *'Education'* sector (Alvarez et al., 2014; Gómez et al., 2016; Ozawa-Meida et al., 2013) comes in second with 9 articles, thereby underpinning academia's growing interest in integrating sustainability into operations within educational institutes. Other important sectors are *'Construction'* (Martinez et al., 2019; Neppach et al., 2017), '*Accommodation and food services*' (Cerutti et al., 2018; Jungbluth et al., 2016) and '*Human health and social work activities*' (Cimprich and Young, 2023; Keil, 2023) which are all represented by 5 articles each. Traditionally low-carbon-impact sectors such as *'Education', and 'Accommodation and food services'* are increasingly focused on due to their environmental effects and expanding sustainability challenges.

This sectoral analysis aligns with the geographical distribution of studies, revealing not only which industries are most studied but also where carbon accounting research is most actively pursued. Europe dominates the research landscape, contributing 35 articles, with Italy (9) (Notarnicola et al., 2023; Rimano et al., 2021), Spain (6) (Bueno et al., 2022; Martinez et al., 2018), and the UK (5) (Ozawa-Meida et al., 2013; Townsend and Barrett, 2015) leading the way driven by proactive environmental policies and carbon-neutral goals (Baehr et al., 2024). Asia follows with 10 articles, notably from Korea (2) (Lee, 2011), China (1) (Chen et al., 2023), Turkey (2), Japan (1) and Indonesia (1) and Thailand (1)

(Forin et al., 2017), reflecting industrial growth and increasing sustainability awareness. . The Americas contribute 9 studies, with Brazil (de Camargo et al., 2019) and Canada (2 each) (Cimprich and Young, 2023) as key contributors, alongside the U.S (Pelton and Smith, 2015), Argentina (Alejandrino et al., 2022), Colombia (Montoya-Torres et al., 2015), and Mexico (Forin et al., 2017) (1 each). Oceania shows some engagement (Demeter et al., 2021), while Africa remains significantly underrepresented, with only one study indirectly linked to Tanzania. This highlights the need for more region-specific research and tools to enhance the global applicability of Scope 3 accounting.

III.2 Methods in Case Studies for Data Inventory and Procurement Emissions Quantification

This section examines key methodologies used for collecting activity data and quantifying carbon emissions specifically associated with procurement activities within an organization. “Activity data” is a quantitative measure of a level of activity that results in emissions (for example, amount spent on purchased goods and services or kilograms of purchased material) (WRI and WBCSD, 2011a).

III.2.1 Methods for Collecting Activity Data and Inventory Compilation

Activity data inventory approaches refer to the methods used to collect activity data for environmental assessments, defining the scale at which the data is gathered. The top-down inventory approach (or inventory-oriented approach), as defined by UNEP (2015), utilizes aggregated data at the organizational level, for example the general procurement of materials irrespective of an allocation to products or activities. The bottom-up (or product-oriented approach) inventory approach is based on the collection of data at a singular product level, for example a product LCA, and then extrapolates organizational inventories and impacts by multiplying the results by the number of all purchased products. Although both approaches aim to deliver the same results, differences in scope and system boundaries may lead to variations in their outcomes. Some processes from supporting activities may not be included in product LCAs and must therefore be added separately. The bottom-up approach provides more detailed, product-level insights, making it valuable for specific analytical assessments, but it comes with increased complexity. When data gaps in the product-oriented approach are filled through extrapolation from similar products or by modeling theoretical proxy products, since conducting multiple product LCAs can be impractical for complex product portfolios, the resulting method is known as a hybrid inventory approach (UNEP, 2015).

However, the terms “top-down,” “bottom-up,” and “hybrid” are not universally defined across standards and studies, making it essential to clarify their meanings in different contexts. In the Organizational Life Cycle Assessment (OLCA) framework, hybridization refers to a "hybrid inventory approach", which integrates top-down and bottom-up inventory approaches to enhance system completeness (UNEP, 2015). In environmental accounting, EEIO analysis is often cited as a top-down

approach, as it relies on macroeconomic data and sector-level emission factors. In contrast, LCA follows a bottom-up approach, collecting detailed product-level data to model environmental impacts. While both approaches have their strengths and limitations, their differences in data granularity and system boundaries can lead to inconsistencies in environmental assessments. As a result, the hybrid method, also known as Hybrid LCA or IO-LCA, was developed to integrate LCA with EEIO analysis, improving completeness and consistency by combining detailed process-level data with broader economic and environmental information (Suh, 2009). These methodologies, particularly LCA, EEIO, and hybrid approaches, form the foundation of procurement emissions quantification and will be explored in greater detail in the following section. Beyond inventory-level and method-level hybridization, hybridization can also occur at the data level. A "hybrid data" type integrates monetary and physical data, refining emissions calculations by leveraging the strengths of both datasets. Furthermore, within the GHG Protocol, "hybrid method" is defined as the combination of supplier-specific Scope 1 and Scope 2 data with generic data for processes further upstream, which may be derived from industry-average, or mixed data sources (WRI and WBCSD, 2011a). However, in practice, hybrid LCA and GHG hybridization are often used synonymously, even though the GHG Protocol specifically refers to combining supplier-specific data with generic physical or monetary data. In reality, most applications of hybrid LCA involve combining average or generic physical data with EEIO models, rather than strictly using supplier-specific information. This discrepancy highlights the need for clearer distinctions in how hybridization is applied in procurement carbon accounting (Baddley and Rasheed, 2023; Keil, 2023; Kjaer et al., 2015). Given these nuances, this study adopts the term *hybrid inventory approach* for a combination of top-down and bottom-up inventory approaches, *hybrid data* for a combination of physical and monetary data, and *hybrid method* for a combination of LCA and EEIO. Figure 2-16 provides an overview of these inventory collection approaches, illustrating their connections to procurement emissions quantification.

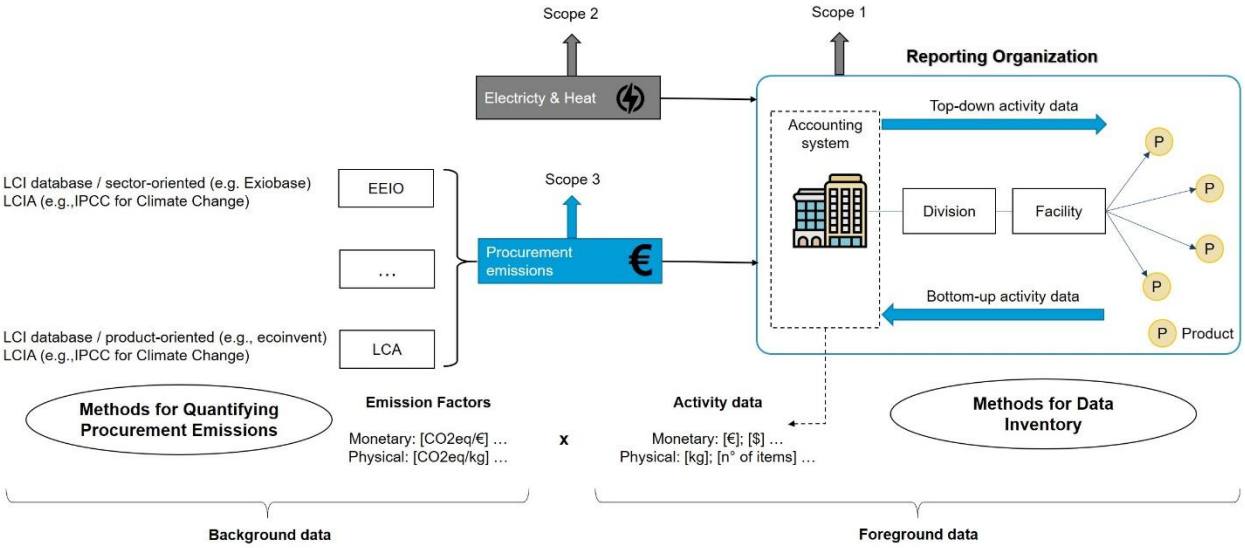


Figure 2-16 Sketch of Methods for Data Inventory and Procurement Emissions Quantification

In the reviewed case studies, 11 articles applied a bottom-up approach, 23 used a top-down approach, 16 followed a hybrid inventory approach, and 4 did not specify an inventory approach or compared multiple approaches. A more detailed breakdown of these findings, including their combination with data types, is presented in Section 2.B.III.3.4.

III.2.2 Methods for Quantifying Procurement Emissions

Building on the methodological foundations introduced in Section 2.A, this section examines the primary methodologies for assessing carbon emissions in procurement, with a focus on Life Cycle Assessment (LCA) and Environmentally Extended Input-Output (EEIO) analysis. It also explores how these approaches have been combined or hybridized in the selected case studies.

Among the reviewed studies, nearly half (46.3%) of the reviewed studies employ LCA, which remains the most widely adopted method for assessing carbon emissions for procurement across multiple sectors. EEIO analysis accounts for 22.2% of the studies, offering a method for evaluating emissions by capturing wider economic interactions and supply chain ties. Furthermore, 20.4% of studies reveal a hybrid method, combining EEIO and LCA, thereby integrating the strengths of both approaches to provide a more comprehensive analysis of carbon emissions. The remaining 11.1% employ various other methods that are unrelated to LCA and EEIO, as they do not demonstrate methodological advancements and present significant limitations. For example, on-site measurements, as applied in certain production sites according to Lee and Cheong (2011) and Lee (2011), are commonly used in greenhouse gas inventories and continuous emission monitoring systems. These measurements account only for suppliers' direct emissions (Scope 1) and emissions from purchased energy (Scope 2), while neglecting a significant portion of indirect emissions across the supply chain (Scope 3). Additionally, assumptions based on supply chain network systems (Chen et al., 2023) (i.e., models that map and analyze the flow of goods, services, and emissions within a supply chain but often rely on approximations and predefined relationships) can introduce inaccuracies, while methods relying on interviews, documentation, or generic GHG Protocol emission factors (Cerutti et al., 2016; Montoya-Torres et al., 2015; Nordman et al., 2024) often lack the granularity and precision needed for a robust analysis. As such, our focus remains on methodologies that provide a more comprehensive and reliable assessment of carbon footprints. A solid understanding of these methodologies related to LCA, EEIO or a combination of both, is essential for identifying the most effective framework to address carbon accounting in organizational purchasing decisions.

Life Cycle Assessment (LCA)

LCA finds diverse applications in the studies reviewed. The most prominent is Product LCA (Bueno et

al., 2022; Georgiou et al., 2019; Harasymchuk et al., 2024), which assesses the environmental impact of individual products across their entire life cycle. In procurement emissions accounting, LCA serves as a methodology for conducting organizational carbon accounting by deriving emission factors for purchased goods and services, supporting carbon footprint calculations at the product and process level.

For example, Cucchi et al. (2023) have enhanced traditional LCA methods by incorporating real-time data derived from Industry 4.0 technologies, thus improving both accuracy and responsiveness in dynamic production environments. Additionally, some studies combine LCA with Life Cycle Costing (LCC) (Alejandrino et al., 2022) or link activity portfolios with Environmental Product Declarations (EPDs) (Manzardo et al., 2018), which extends the scope of environmental evaluations to broader portfolios. Process LCA (de Camargo et al., 2019; Resta et al., 2016), although less common, is employed to evaluate specific stages within a product's life cycle, offering insights into localized environmental impacts.

The reviewed articles highlight several strengths of LCA. It offers an in-depth, comprehensive view of environmental impacts throughout every stage of a product's life cycle (Jungbluth et al., 2016; Marx et al., 2020; Notarnicola et al., 2023), proving to be crucial for evaluating carbon emissions in organizational procurement. LCA supports procurement decisions by offering emission factors for purchased goods and services, helping organizations align procurement strategies with sustainability goals. It also enables organizations to track their environmental performance, identify areas for improvement (Bueno et al., 2022; Toniolo et al., 2023), and detect environmental hotspots within their supply chains (Manzardo et al., 2018) while delivering detailed data with high granularity (Resta et al., 2016). This level of insight helps in defining materiality (Forin et al., 2017) and supports detailed environmental reporting, in line with corporate sustainability objectives and regulatory requirements.

However, LCA does have some limitations. A common challenge is the presence of data gaps (Cucchi et al., 2023), particularly for small-scale procurement items (Cerutti et al., 2018), which often require assumptions and can compromise the accuracy of the analysis. This is especially relevant in procurement emissions accounting, when data availability for specific purchased goods is limited, leading to reliance on generic databases that may not reflect actual supply chain conditions. LCA also requires a detailed knowledge and expertise of the methodology (Marx et al., 2020). Carrying out an LCA can be time-consuming and resource-intensive as well as requiring specialized software and databases (Neppach et al., 2017), which underlines the significance of careful planning and resource allocation during these assessments. Furthermore, the quality of input data is critical for reliable results (Alejandrino et al., 2022), and reliance on generic datasets can oversimplify and provide less nuanced

insights (de Camargo et al., 2019).

Environmentally Extended Input Output (EEIO)

While LCA is the most widely used methodology for evaluating carbon emissions in organizational procurement, EEIO has emerged as a complementary approach by capturing broader economic interaction, particularly for sectors that LCA may overlook, such as services. Some studies suggest applying LCA and EEIO differently depending on the type of purchase. For instance, LCA is typically used to assess Scope 2 emissions from purchased electricity and fuels, where high-precision, process-based data is available (Demeter et al., 2021; Herth and Blok, 2023). Conversely, EEIO is more suitable for estimating emissions from purchased goods and services, which are often challenging to track at the product level but benefit from EEIO's broader economic perspective (Kjaer et al., 2015). EEIO assesses environmental impacts across different economic sectors by analyzing monetary flows and inter-sectoral linkages using, relying on the Leontief equation (as seen in Equation 2-2) (Leontief, 1974): $x = (I - A)^{-1} y$; where (A) is the technology matrix, $(I - A)^{-1}$ is the Leontief inverse matrix expressing the total production (direct and indirect) of each sector required to satisfy the final demand (y) and (x) is the total production of goods and services. The EEIO analysis process can be illustrated in three key steps:

- **Data Collection**: Organizations gather expenditure data from procurement records and financial systems to represent all relevant activities,
- **Sector Mapping**: Purchases are matched to the corresponding economic sector, allowing the application of sector-average emission factors,
- **Emissions Calculation**: Total impacts are derived by multiplying sector-specific emission factors with expenditure data, enabling the assessment of indirect emissions.

EEIO is particularly valuable when detailed procurement data is unavailable (Stridsland et al., 2023a). It offers a holistic view of supply chain emissions and supports carbon accounting, reporting and sustainable procurement (Townsend and Barrett, 2015). Monetary emission factors derived from EEIO are both easy to implement and cost- and time-effective for integration into current systems (Martinez et al., 2018). Compared to process-based LCA, EEIO minimizes truncation errors by covering entire supply chains, incorporates sector-wide data, and aligns well with corporate sustainability reporting frameworks (Gómez et al., 2016; Lo-Iacono-Ferreira et al., 2017). It also provides sector-specific insights, meets completeness and reproducibility requirements (Alvarez et al., 2014), and supplies transparent data, which is cross-checked against national accounts (Martinez et al., 2019).

Despite its advantages, EEIO lacks product-level specificity, making it less suitable for evaluating individual purchases with high material variability (Martinez et al., 2019). Sectoral aggregation

introduces uncertainties, as companies with diverse procurement activities may not fit neatly into predefined categories (Alvarez et al., 2014). Additionally, the presence of mis-coded or unclassified data can introduce inaccuracies in emission estimates (Stridsland et al., 2023a). The method's reliance on national sector-average emission factors results in low granularity (Gómez et al., 2016), often failing to reflect local consumption patterns. EEIO assumes homogeneity within sectors, meaning all firms in a given industry are assigned the same emission factor, which may not reflect real-world variations (Townsend and Barrett, 2015). Another limitation is the temporal difference between company data and EEIO datasets, which are typically updated on a yearly or multi-year basis (Anthonissen et al., 2015; Martinez et al., 2019; Yu et al., 2020). This challenge also applies to LCA, as background databases are often not updated in real time, potentially leading to discrepancies in procurement emissions estimates, although none of the selected studies explicitly mentioned this limitation. Additionally, value-based pricing inconsistencies can cause overestimation of emissions, particularly in industries where cost does not correlate with material and energy inputs, such as pharmaceuticals (Aigner, 2024). These challenges highlight the need to complement EEIO analysis with more detailed methods to achieve a more nuanced and accurate understanding of environmental impacts.

Hybrid Data and Hybrid Methods

Given the respective strengths and limitations of LCA and EEIO, hybrid methods have emerged as a comprehensive approach to procurement emissions quantification. By integrating process-specific accuracy from LCA with the broader economic coverage of EEIO, these methods enhance completeness while minimizing data gaps and truncation errors. Hybridization allows for a more refined assessment, balancing sector-wide insights with product-level specificity, making it particularly useful for complex procurement systems. The choice of hybridization level depends on data availability and system complexity, and this section explores how these methods have been applied in the selected case studies.

(a) Cross-Validating EEIO with LCA

In a recent study, Keil (2023) applies hybrid procurement emission accounting method in which products are assigned to economic sectors within two EEIO databases (e.g., Exiobase and WIOD), to estimate upstream emissions. If discrepancies arise between EEIO estimates, data from existing process-based LCA studies are applied to refine the results particularly in industries requiring product-specific precision, such as pharmaceuticals. This method helps analyze procurement emissions with greater accuracy, but challenges such as defining system boundaries, non-transparent emission reporting from suppliers, and data availability issues can impede the effectiveness of the methodology.

(b) Combining LCA and Monetary-Based Approaches

A key advancement in assessing carbon emissions related to procurement lies in hybrid methodologies that integrate multiple accounting approaches, allowing organizations to tailor their approach based on data availability. Within the OLCA framework, which establishes a baseline for comprehensive, multi-criteria assessment across an organization's value chain, Finogenova et al. (2019) emphasized the need for a universal inventory analysis approach and proposed a flexible methodology that integrates two primary accounting methods:

- Macroscopic (monetary-based approach: estimating emissions from EEIO data using sector-specific averages),
- Microscopic (product or process-based approach: estimating emissions using internal or generic LCA).

This approach adheres to OLCA principles by enabling integration of diverse data types to compile a more complete and organization-wide environmental inventory. It allows companies to select the most suitable accounting method for each purchase depending on data availability, making carbon emission calculations and sustainability reporting more accessible, particularly for smaller enterprises with limited internal datasets. Additionally, by integrating different methods, a more comprehensive inventory of indirect activities can be compiled, facilitating the identification of environmental impact hotspots. However, this flexibility comes with challenges, including the risk of double counting and discrepancies in data quality. The reliance on various data sources, such as internal LCA studies and databases like DEFRA (UK Department for Environment, Food & Rural Affairs), introduces further complexities, particularly when data consistency is lacking. Furthermore, the hybrid approach may be limited in the scope of environmental impact categories it can quantify, which could restrict the comprehensiveness of the assessment.

Building on this concept, but diverging from the OLCA standard, Cimprich and Young (2023) propose an adaptation that enhances procurement-related emission assessments by integrating process-based LCA data with financial data. Their approach focuses on a statistically representative sample of purchased products, which is then scaled to an organization-wide level. By multiplying in-house environmental intensity data (e.g., kg CO_2 per dollar spent) with financial expenditures (e.g., dollar spent), the approach offers a clearer understanding of the environmental assessment and detailed product-level granularity while still generating system-wide insights. Unlike traditional EEIO analysis, which relies on aggregated sectoral data, their method preserves the precision of process-based LCA while offering broader applicability. This approach proves particularly useful for identifying supply chain hotspots and can be adapted to different sectors. However, it also presents limitations, such as reliance on data quality and potential overgeneralization to other institutions. Due to lack of LCA data for some categories (e.g., pharmaceuticals), their environmental impacts were estimated using the

EEIO approach.

Both hybrid methodologies pinpoint the importance of balancing accuracy with scalability in carbon footprint assessments. By strategically integrating LCA and monetary-based methods, organizations can refine their sustainability strategies.

(c) Combining LCA and Monetary-Based Approaches with Supplier-specific data

A further refinement of the hybrid data approach integrates three levels of data:

- Macroscopic (monetary-based approach: estimating emissions from EEIO data using country- or sector- specific averages),
- Mesoscopic (estimating emissions using supplier-specific emission intensities at the organizational-level),
- Microscopic (product or process-based approach: estimating emissions using internal or generic LCA).

This methodology enables a more detailed analysis of emissions by integrating data from various levels of the supply chain (Baddley and Rasheed, 2023; Paepe et al., 2023). This methodology integrates multiple data layers to capture emissions across different accuracy levels and to make meaningful comparisons. Using supplier-specific data allows for a more tailored and accurate representation of carbon footprints across different suppliers, improving procurement-based carbon accounting by increasing precision (Baddley and Rasheed, 2023; Paepe et al., 2023). However, while integrating supplier carbon intensities is a valuable step, the majority of existing studies have not yet utilized supplier-specific data at the product level in a hybrid method. Instead, they typically rely on supplier data at the organizational level (i.e., emission intensities) rather than on individual products or processes (i.e., emission factors), which limits the granularity and accuracy of carbon footprint assessments. Moreover, this methodology faces challenges, particularly the difficulty in distinguishing between similar commodities with different carbon footprints, as classification systems lack sufficient granularity (Paepe et al., 2023). In this case, the use of UK-based proxies, rather than regionally specific data, introduces potential misrepresentation of local carbon intensities. However, this limitation reflects the data choices made in the study, rather than a methodological flaw inherent to the EEIO approach itself (Baddley and Rasheed, 2023). Additionally, lower costs could lead to mis-estimations of emissions.

(d) Interpreting Procurement Case Studies through Hybrid LCA Methodologies

The procurement quantification methods identified across the reviewed case studies can be classified according to the hybrid LCA typologies described in Section 2.A.V, based on how they integrate process-based, monetary, and supplier-level data.

The cross-validation approach proposed by Keil (2023), which uses LCA data to refine EEIO-based emission estimates in selected sectors, aligns most closely with the Classic Tiered Hybrid LCA (THL) model. In this method, EEIO forms the backbone of the assessment, providing broad sectoral coverage, while LCA is selectively applied to improve resolution in key product categories. Although the method shares conceptual similarities with the Path Exchange approach, it does not involve a formal disaggregation or replacement of IO matrix elements. Instead, it reflects the flexible and targeted integration logic characteristic of classic THL, without standardized computational correction mechanisms.

The methodology described by Finogenova et al. (2019), which combines process-level and monetary-based data streams based on availability, also fits within the Classic Tiered Hybrid LCA framework. This approach allows organizations to switch between EEIO-based estimates and internal LCA results depending on data availability, echoing the adaptable nature of tiered hybridization. However, the lack of a unified structure or automation logic distinguishes it from more advanced hybrid models. It provides a pragmatic, low-barrier entry to hybrid accounting, particularly for small- and medium-sized enterprises, while still reducing truncation errors in key procurement categories.

In contrast, the scalable framework proposed by Cimprich and Young (2023) is more methodologically structured and reflects the logic of Systematic Tiered Hybrid LCA (STHL). Their approach uses process-based environmental intensities applied to a statistically representative sample of products, which are then extrapolated across financial data. This systematic scaling and reproducibility, along with the ability to automate some aspects of the hybridization process, align well with STHL's objectives. The method offers a balance between precision and scalability, supporting both detailed assessments and broader organizational decision-making.

Finally, the approach combining monetary, supplier-specific, and process-based data (Baddley & Rasheed, 2023; Paepe et al., 2023) can be understood as a hybrid of two advanced methods: Matrix Augmentation (MA) and Systematic Tiered Hybrid LCA (STHL). The integration of supplier-specific emission intensities to refine EEIO sector averages is a hallmark of the MA approach, which creates more granular representations of economic sectors. Simultaneously, the layered structure, combining macroeconomic, mesoscopic, and process-level data, requires a systematic and transparent application framework, reflecting key characteristics of STHL. Although these studies move toward deeper hybridization, they fall short of the full matrix integration typical of Integrated Hybrid LCA (IHL), as they retain layered data processing rather than solving for a single system-wide matrix.

In sum, while all case studies apply hybrid logic, their methodological alignment varies by structure, data granularity, and integration depth. Mapping them to the appropriate hybrid LCA methods clarifies

how different strategies can support accurate and scalable procurement emission assessments.

III.3 Carbon Accounting Practices in Case Studies

This section outlines key tools, data types, databases, and methodological choices involved in assessing procurement-related emissions at the organizational level. It follows a structured approach based on the LCA framework, starting with goal and scope definition, followed by inventory analysis and impact assessment methods.

III.3.1 Classification and Analysis of Case Study Goals

Every case study should be guided by a clear goal and scope definition and employ methods appropriately selected to achieve those goals (ISO 14072, 2024; UNEP, 2015). To facilitate an analysis between the goals of all studies in this review, all individual goals were consolidated into 11 generic goals defined by the OLCA standard based on a deductive analysis, shown in Table 2-6. Most case studies pursued multiple goals, but due to inconsistent descriptions, clear prioritization was not possible. While 57% focused exclusively on carbon emissions, the rest adopted a multi-criteria approach, linking their objectives to broader environmental impact categories beyond carbon.

Based on the OLCA standard, goals can be either analytical, managerial or societal. Analytical goals deliver quantified results for environmental hotspots and reduction opportunities and therefore enable environmental performance improvements. Furthermore, they act as information for decision-making in managerial goals like improving organizational procedures, environmental communication through reporting and showing environmental awareness with marketing. Societal goals influence stakeholders outside of the analyzed organization, ideally initiating or improving sustainable development through the reduction of pressure on the environment or the enhancement of environmental tools in the supply chain (UNEP, 2015).

Table 2-6 shows that the primary goals across all case studies are the identification of environmental hotspots, support for strategic decision-making, and the reduction of environmental impacts—addressing analytical, managerial, and societal perspectives. Secondary objectives include understanding risks, identifying mitigation opportunities, improving internal processes, and tracking performance. In contrast, goals such as cost reduction, stakeholder motivation, and support for functions like marketing or supply chain management are mentioned less frequently.

Table 2-6 Classification of Identified Goals in the Selected Case Studies According to OLCA Goals (UNEP, 2015)

Goal category	Goals	N^{O} of Goals
Analytical	Identify environmental hotspots	26
	Understand risks and impact reduction opportunities	16
	Gain insights in internal operations and value chain	8
	Track environmental performance	11

Goal category	Goals	N° of Goals
Managerial	Get support for strategic decisions	25
	Improve organizational procedures	10
	Show environmental awareness with marketing purposes	8
	Get the basis for environmental communication with stakeholders and reporting	6
	Reduce operational costs	4
Societal	Reduce pressure on the environment	20
	Enhance environmental tools within stakeholders	3

III.3.2 Standards Employed in Case Studies

The choice of standards is essential in structuring procurement carbon accounting assessments, as it influences the methodology, scope, and types of environmental impacts adressed. The reviewed case studies reflect a diversity of standards, each with distinct requirements, scopes, and levels of methodological specificity (Figure 2-17).

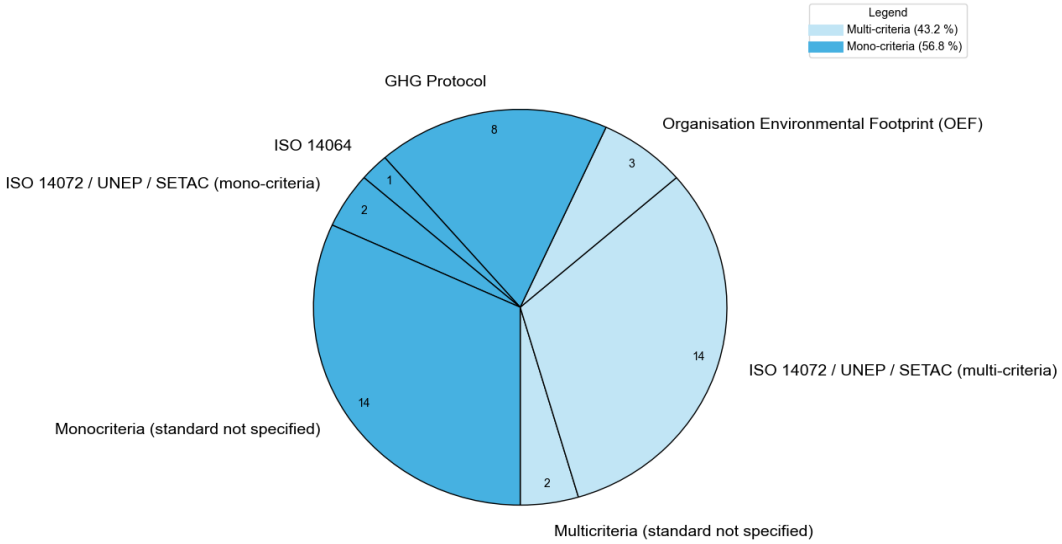


Figure 2-17 Employed Standards Across Studies

Among the reviewed articles, 16 studies followed the Organizational LCA (OLCA) approach following either the ISO 14072 or UNEP guidelines (Cimprich and Young, 2023; Finogenova et al., 2019; Marx et al., 2020). In contrast, eight studies applied the GHG Protocol, which adopts a mono-criteria approach focused solely on GHG emissions (Baddley and Rasheed, 2023; Keil, 2023; Stridsland et al., 2023a). Only one study explicitly followed a comparable ISO standard, namely ISO 14064, which also focuses on carbon footprint quantification (Harasymchuk et al., 2024).

A smaller set of studies (n = 3) employed the European Commission's Environmental Footprint (OEF) method, which supports a broader life-cycle-based and multi-criteria impact assessment ((Martinez et al., 2019, 2018; Neppach et al., 2017).

Additionally, 16 studies did not reference any specific standard, yet conducted environmental impact assessments on procurement categories or supply chains. Of these, 15 studies adopted a mono-criteria approach, limited to GHG emissions (Cerutti et al., 2018; Nordman et al., 2024; Townsend and Barrett, 2015), while two studies employed multi-criteria frameworks to evaluate additional impact categories (Pelton and Smith, 2015; Wiedmann et al., 2009)

Overall, 56.8% of the reviewed articles focused on greenhouse gas emissions in a mono-criteria approach, while 43.2% employed a multi-criteria approach. Although the ISO 14072 or UNEP standards (ISO 14072, 2024; UNEP, 2015) offer a framework for multi-criteria evaluation, they also allow for single criterion assessments, as demonstrated by Rimano et al. (2021) and Finogenova et al. (2019).

The predominance of mono-criteria approaches, particularly those focused solely on GHG emissions, is largely driven by their practical advantages, policy relevance, and compatibility with climate-related targets. Carbon accounting aligns closely with regulatory frameworks and corporate ESG disclosure expectations, making it the most accessible and actionable entry point for many organizations. These approaches are also comparatively less resource-intensive, requiring fewer data inputs and offering faster implementation, especially useful in procurement contexts where supplier-specific information is often unavailable.

However, while carbon is a critical metric, it represents only one dimension of sustainability. A meaningful sustainability assessment should encompass a broader set of environmental indicators (e.g., water use, land use, toxicity), as well as social dimensions (e.g., labor practices, community impacts) and economic factors (e.g., value creation, cost efficiency, equity). These dimensions are essential for ensuring that emission reductions are not pursued at the expense of social justice, economic resilience, or ecological integrity. Multi-criteria approaches, though less commonly applied due to their complexity and higher data demands, provide the necessary framework for addressing these interlinked challenges.

Ultimately, prioritizing carbon emissions may support short-term reporting goals, but advancing genuine sustainability requires a holistic perspective that integrates environmental, social, and economic impacts into procurement assessments and decision-making processes.

III.3.3 System Boundaries of Procurement in Case Studies

The classification of general system boundaries differs depending on the applied standard. The GHG Protocol primarily defines system boundaries based on direct emissions (Scope 1), indirect emissions from purchased energy (Scope 2), and indirect emissions from up- and downstream activities (Scope 3) to provide a comprehensive view of organizational emissions. However, this framework does not highlight a detailed product-specific system boundary for procurement emissions. Conversely, the

OLCA approach focuses primarily on the organization's total product life cycles, incorporating supporting organizational activities as extensions. This structure enables a better overview of product-related emissions. The analysis of procurement impacts necessitates a precise product-specific system boundary. Since this review focuses on upstream procurement processes, included case studies use a *cradle-to-gate* system boundary, encompassing processes from raw material extraction and pre-production up to the factory gate of the case study organization. To broaden the research scope, we also analyzed whether case studies include product-related downstream emissions from *gate-to-grave* activities, such as the use and end-of-life phases, as these are often directly linked to the type of products or materials procured (e.g., energy efficiency or recyclability). The *cradle-to-gate* and *cradle-to-grave* system boundary concepts originate from the product-level LCA framework and were later adopted by the OLCA standard. To align the description of Scopes with the OLCA terminology, product-related and supporting activities from the GHG Protocol were classified as *cradle-to-gate* or *gate-to-grave* activities as shown in Table 2-6. Challenges arising from the use of a product-based system boundary nomenclature in organizational-level assessments are examined in the discussion (UNEP, 2015; WRI and WBCSD, 2011a).

Table 2-7 OLCA and GHG Protocol System Boundaries (UNEP, 2015; WRI & WBSCD, 2011)

OLCA System Boundary / **GHG System Boundary**		**Cradle-to-gate**	**Gate-to-grave**
Scope 1 (direct emissions)		x	
Scope 2 (emissions from purchased energy)		x	
Scope 3 (Upstream)	3.1 Purchased goods and services	x	
	3.2 Capital goods	x	
	3.3 Fuel and energy related activities	x	
	3.4 Upstream transportation	x	
	3.5 Waste generated in operations	x	
	3.6 Business travel	x	
	3.7 Employee commuting	x	
	3.8 Upstream leased assets	x	
Scope 3 (Downstream)	3.9 Downstream transportation		x
	3.10 Processing of sold products		x
	3.11 Use of sold products		x
	3.12 End-of-life of sold products		x
	3.13 Downstream leased assets	x	
	3.14 Franchises	x	
	3.15 Investments	x	

Our analysis shows that 72% of selected case studies only adopted the *cradle-to-gate* system boundary for evaluating procurement impacts, while 28% included *gate-to-grave* impacts. Although the prominent OLCA standard in our selection requires a justification for excluding downstream activities, our search query, focused on procurement and the upstream supply chain, may be biased towards

cradle-to-gate studies (UNEP, 2015). Notably, the GHG Protocol, as the second most applied standard in our selection, does not require the inclusion of downstream activities nor a justification of omission in its current form (WRI and WBCSD, 2011a).

III.3.4 Data Types and Inventory Approaches

As explained in section 2.B.III.2.1, various inventory approaches and data types can be distinguished. Physical data (e.g., quantities, mass, consumption) and monetary data (e.g., costs, basic price, purchase price) can be used independently. If both data types are combined to address data gaps, they form a hybrid data type (WRI and WBCSD, 2013).

With 23 case studies, most authors used the top-down inventory approach for procurement emissions. Out of these 23, 14 collected only monetary top-down data (Herth and Blok, 2023; Keil, 2023; Lo-Iacono-Ferreira et al., 2017) and 8 collected physical top-down data (Alejandrino et al., 2022; Rimano et al., 2021; Toniolo et al., 2023), while only Neppach et al., (2017) tried to employ the top-down inventory approach with hybrid data (Figure 2-18). However, a closer examination of studies using monetary data pinpoints the variability in the definition of monetary data. Not specifying whether the study uses basic prices, costs, or purchase prices significantly impacts the interpretation and reproducibility of results. Additionally, tax inclusion in monetary values varies geographically, with some countries (e.g., those in Europe) including taxes while others (e.g., the USA and Canada) exclude them. This variation underscores the need of clearly specifying the type of monetary value used in studies to ensure accuracy and comparability in hybrid data or purely monetary approaches. In contrast, the bottom-up inventory approach was only used with physical data. The bottom-up approach was used by 11 studies and is therefore significantly less prominently used than the top-down approach (Bueno et al., 2021; Chen et al., 2023; Nordman et al., 2024).

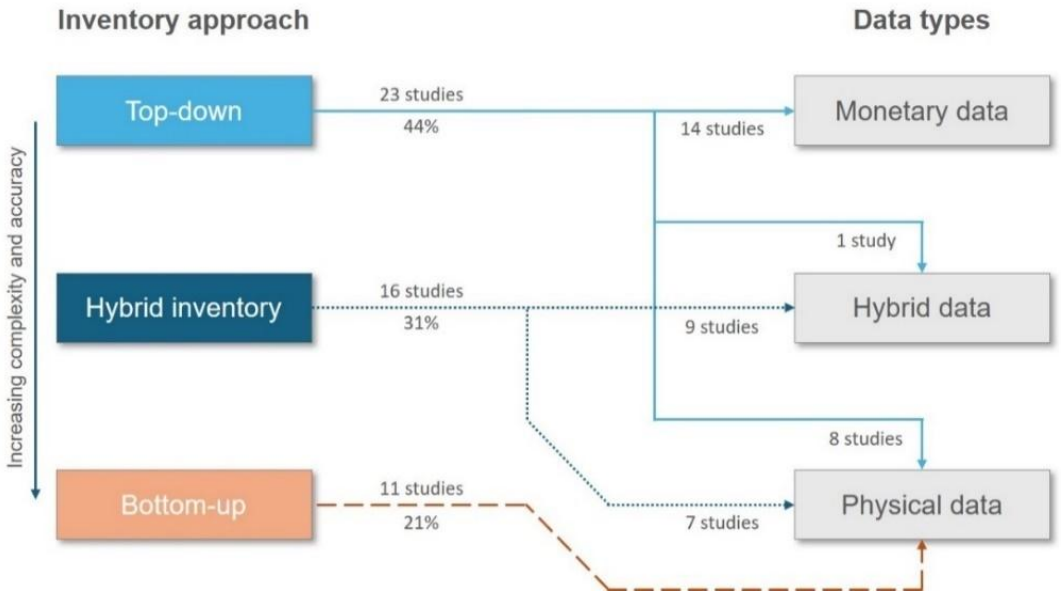


Figure 2-18 Combinations of Data Collection Approaches and Data Types

The hybrid inventory approach, with a combination of top-down and bottom-up inventories, was adopted by 16 case studies. 7 hybrid case studies solely used physical data to fill data gaps like de Camargo et al. (2019), who used bottom-up data from representative products of the organization's portfolio to extrapolate data to the entire portfolio. 9 case studies collected physical as well as monetary data for a hybrid data approach. Notable in this category are Cimprich and Young (2023), who used monetary data in the health care sector to extrapolate where physical data was not available and Finogenova et al. (2019), who calculated the global warming potentials with physical data from available LCA studies but broadened the scope to calculate acidification and water use impacts with the help of monetary data. In two case studies from Pelton and Smith (2015) and Demeter et al. (2021), multiple inventory approaches and data types were utilized to compare results.

III.3.5 Data Sources

In the context of this research, foreground data sources refer to activity data that is directly collected from an organization’s procurement activities, such as procurement records, and financial statements. These sources represent primary data used for carbon accounting. In contrast, background data sources provide emission factors and environmental impact data from established databases, literature, or models, filling gaps where data is unavailable. Figure 2-16 illustrates the distinction between foreground and background data sources. These sources enable organizations to assess procurement-related emissions within Scope 3 using different types of data, as explained in section 2.B.III.3.4.

Foreground Data

The first step for the calculation of environmental impacts at an organizational scale is the collection of activity (or foreground) data. As data availability can be a challenge, this time-consuming step can often dictate the application of certain methods and influence the accuracy of final results. Therefore, most studies do not rely on a single foreground data source for procurement data but combine data from multiple sources to improve data availability. However, the integration of these sources often introduces challenges related to differences in consistency and granularity that can influence the robustness of the assessment (Bueno et al., 2022; Yu et al., 2020).

The most common source are records from accounting and procurement departments with a share of 33%, including invoices, stock inventories and other procurement data. These sources can either be used for monetary or physical data types. Internal documents like technical sheets, reports, archival documents and manuals, which are especially useful for physical data types, account for a share of 10%. Data from suppliers and manufacturers as well as surveys and interviews have a share of 9%, while literature sources account for a share of 8%. On-site data from measurements and material flow analysis, assumptions, and data from Enterprise Resource Planning (ERP) or Material Resource Planning (MRP) software each account for 7%. Less common foreground data sources below a share of 5% are statistics, environmental management systems, and IoT technologies. Noticeably, two case studies from Lee and Cheong, (2011; Lee, 2011) with the Hyundai Motor Company employed the on-site measurement approach.

Background Data

Background data from established databases is crucial for generating emission factors, which serve as key inputs for procurement carbon accounting. These emission factors quantify environmental impacts per unit of activity (e.g., kg CO_2 per € or per kg of material) and are later multiplied with foreground activity data to assess the carbon footprint of procurement activities. Emission factors are derived from previous LCA and Environmental Product Declarations (EPDs), which account for 13% of the case studies. Scientific literature, another key source of emission factors, was used in 18% of the studies. Additionally, government reports and industry-specific studies contribute to the development of emission factors used in procurement assessments (5% of the case studies). Beyond these sources, background databases are widely used to generate emission factors, filling gaps where primary or literature-based data is unavailable. The most commonly used database is ecoinvent, referenced in various iterations, with a 28% share. The “UK Government GHG Conversion Factors for Company Reporting” dataset from DEFRA contributes 8%, while the EEIO databases from the US EPA and Exiobase both hold a 9% share. The WIOD database is used less frequently, appearing in 5% of cases. Other sources include IPCC emission factors with a share of 5%. Additionally, several case studies

incorporated regional or sector specific databases to enhance accuracy. This was adopted by Yu et al. (2020) with the Australian National Life Cycle Inventory Database (AusLCI) or the WRI Cool Food Pledge data in Nordman et al. (2024).

It is noteworthy that, despite its widespread use in professional practice, the CEDA database is rarely cited in academic literature. This may be attributed to its restricted accessibility or commercial pricing model, which poses a barrier for academic institutions and researchers with limited licensing budgets.

III.3.6 Classification Systems for Procurement Data

Organizations classify their purchases into specific categories to link them to spend-based emission factors, particularly when using EEIO method to gain a clear overview of their spending and the associated impacts. This classification could be done using either an internal codification system or a standardized system. When assessing carbon footprints for procurement, effective data classification using a predefined system is essential. Based on our review, these codes can be broadly classified into two main categories: those facilitating the classification of activities and those facilitating the classification of products and services. The reach of use varies from national to international use.

For example, the NACE system, used in the EU as a statistical classification of economic activities, appears in four articles. Other systems include NAICS (North American Industry Classification System) and ANZSIC (Australian and New Zealand Standard Industrial Classification), which are region-specific and activity-based, whereas UNSPSC (United Nations Standards Products and Services Code) and HS (Harmonized System) are international and focused on products and services. The ISIC (International Standard Industrial Classification) is an international system; though widely applied, this review highlights that it is most heavily used in the UK, in particular in combination with DEFRA and EEIO tables (Ozawa-Meida et al., 2013; Townsend and Barrett, 2015). Additionally, systems such as NACRES (Nomenclature for Research and Higher Education Purchases in France) are highly specialized for specific sectors and regions. Some organizations also choose to use internal classification systems or other factors derived from the accounting field. Notably, a large proportion (39) of the articles did not specify the classification system used.

III.3.7 Impact Assessment Methods

Studies in our selection using physical foreground data need to select impact assessment methods to calculate environmental impacts. Even though the selection of these methods can heavily influence results (Chen et al., 2021), only 57% of all case studies fully specified the applied impact assessment methods, while 25% specified no methods and 8% partly specified the applied method. If case studies were modeled to work with monetary data and EEIO-tables, the underlying impact assessment methods were not chosen by the authors but instead by those responsible for the creation of the

applied EEIO databases. This complicates the understanding of the importance of impact assessment methods for those implementing spend-based methods. Therefore, the subset of studies employing monetary data types, either in combination with physical data or as the single data type, shows a higher percentage of 31% for implementations not specifying any impact assessment methods and 15% for studies partly specifying the methods, compared to the results across all case studies stated above.

Some authors may choose multiple impact assessment methods depending on the impact category. Of all stated impact assessment methods, the IPCC global warming potentials were the most common with a share of 28%. The ReCiPe midpoint method has a share of 20%, while the ReCiPe endpoint method only has a share of 7% of all applied methods. Another common method is CML with a share of 15%, while TRACI, the European Environmental Footprint (EF), IMPACT and CED only account for a share of 4% each. While most methods are applied globally, the TRACI-method originating from the Environmental Protection Agency (EPA) has a clear application focus in North America, while the European EF-method stemming from the European Commission is solely applied in Europe across our selected case studies.

III.3.8 Software and Tools Used in Procurement Carbon Accounting Studies

In the context of procurement carbon accounting, software is mainly used for carbon footprint calculations or emission factor creation. The following analysis explores the distribution of software tools in the reviewed studies, highlighting their specific applications.

The distribution of software and tools in the reviewed studies reveals that a considerable number of case studies (22) did not specify the software used. Among the specified tools, *Microsoft Excel* (Baddley and Rasheed, 2023; Chen et al., 2023; Townsend and Barrett, 2015) is identified as the most frequent data analysis tool used to perform basic data analysis in carbon accounting and sustainability research, appearing in 11 studies. Other data analysis tools include *R* (Nordman et al., 2024) and *Python* (Paepe et al., 2023), each being highlighted in one study to point out their application in working with large datasets, performing complex calculations, or creating emission factors.

LCA software was employed in the reviewed case studies to create emission factors of purchased products, though the case studies did not clearly highlight or justify their choice of tools. Among LCA software, *SimaPro* was the most frequently used, appearing in 10 case studies (de Camargo et al., 2019; Forin et al., 2019), followed by *Sphera* in 5 studies (Marx et al., 2020; Rimano et al., 2021) and other LCA tools, such as *OpenLCA* (Bueno et al., 2022; Cimprich and Young, 2023) (2 studies) and *Umberto* (Forin et al., 2019) (1 study).

Additionally, other tools have been used to extract pre-defined emissions factors and could be classified as sector-specific (e.g. *Sustainable Textile Assessment Tool*) (Resta et al., 2016) referred to in two studies or country-specific tools (e.g. EEIO based tools such as *OpenIO US, OpenIO Canada, and MiLCA*) (Forin et al., 2019; Pelton and Smith, 2015), cited in 3 studies. These highly specialized tools imply studies for sectors or very specific geographic contexts that need specific data for assessment.

The high number of studies (22) not specifying the software used indicates a potential reporting gap and, as a result, future studies should try to disclose the tools used with greater transparency, so that replicability and comparability across research can be assured.

IV. Discussion

This review provides a comprehensive analysis of different methods used in the selected case studies to account for Scope 3 carbon emissions in the context of organizational procurement, emphasizing the need for robust, accurate and transparent approaches in addressing emissions reporting challenges. By analyzing LCA, EEIO, and various hybrid approaches, the findings offer practical insights into overcoming limitations in emission reporting procedures, matching organizational strategies with regulatory standards, and filling significant deficiencies in current methodologies.

IV.1 Inconsistencies in Procurement Emission Calculations

Inconsistencies in procurement carbon accounting stem from methodological variations, differing standards, and inconsistencies in case study applications, all of which reduce reproducibility and confidence in results. Many studies do not properly disclose the methodology, impact assessment method, system boundaries, inventory approaches, the software, classification systems, or assumptions employed in emissions calculations, making verification difficult. Furthermore, some studies omit entire procurement categories or fail to justify missing procurement-related emissions, particularly within GHG Protocol case studies. As regulatory requirements like the European CSRD increase transparency demands, many organizations are struggling to align their emissions assessments with these expectations. According to Baehr et al. (2024), lack of transparency creates inconsistencies in Scope 3 carbon accounting practices, highlighting the need of having harmonized and transparent reporting frameworks and consistent application of methodologies to improve transparency and help in meeting regulatory requirements. Additionally, the reliance on generic databases often results in inaccurate emission inventories that fail to reflect actual procurement activities. Differences in monetary data treatment, such as using basic prices versus purchase prices that include taxes and transport costs, further distort emissions estimates (Baddley and Rasheed, 2023). Variability in how electricity purchases are classified (Scope 2 vs. Scope 3) also leads to inconsistent reporting (Baddley and Rasheed, 2023). Given these challenges, most inconsistencies can

be attributed to methodological differences and variations in standards, which are explored in IV.1.1 and IV.1.2.

IV.1.1 Inconsistencies in Methodologies

Methodological inconsistencies in procurement emission calculations primarily stem from variations in data quality and availability (i.e., foreground and background data) and modeling approaches, which significantly impact the accuracy and comparability of Scope 3 accounting.

A major challenge is the limited availability and inconsistent quality of supplier-specific data, as many organizations lack access to detailed, reliable emission data from their supplier. Even when supplier-specific data is collected, it is often incomplete, prone to human error during data entry, processing, or interpretation (Ozawa-Meida et al., 2013). Miscommunication between suppliers and organizations, can further degrade the quality of emissions data (Forin et al., 2017). This issue is especially noticeable in companies with diverse product portfolios, where assumptions, proxies, and human error cause inaccuracies. According to Vieira et al. (2024), only about one-third of companies collect supplier-specific data, and even then, it is limited to approximately 40% of suppliers on average.

Additionally, reliance on secondary data and assumptions introduces uncertainties and undermines the validity of reported inventories, as many methodologies use generic emission factors from databases that may not reflect actual supply chain conditions (Baddley and Rasheed, 2023). Some studies rely on generic sector-based emission factors, while others use detailed product-specific data, resulting in significant discrepancies in emission estimations. This issue is further compounded by the lack of standardized emission factors for all purchases or a universally accepted methodology (Anthonissen et al., 2015; Chen et al., 2023; Forin et al., 2017).

Inconsistencies in procurement emission calculations also arise due to differences in methodologies, particularly between the varying scope of LCA and EEIO methods. The EEIO method relies on aggregated economic data and sectoral emission factors, offering broad coverage at a macro level but often lacking specificity at the product or supplier level. Conversely, the LCA method builds emissions inventories from detailed product-level data, providing high accuracy but requiring extensive data collection efforts (Alejandrino et al., 2022; Jungbluth et al., 2016). The scope of these methodologies further diverges, as EEIO models primarily capture economic transactions and sector-wide emissions, while LCA focuses on product-specific life cycle impacts, leading to differences in boundary setting and allocation rules (Cerutti et al., 2018; Yu et al., 2020). These methodological differences create inconsistencies in system coverage, where EEIO-based studies provide a comprehensive but less granular view of procurement emissions, while LCA-based approaches can yield more precise results but may lack full supply chain coverage. Additionally, hybrid models attempting to integrate EEIO with

LCA face challenges in reconciling different data resolutions, system boundaries, and allocation methods, often leading to inconsistencies in reported emissions for the same procurement activity (Baddley and Rasheed, 2023; Forin et al., 2017).

Moreover, temporal misalignment between datasets and real-time procurement data leads to discrepancies as emission factors from EEIO models or Life Cycle Inventories (LCIs) may not capture recent changes in supply chain activities, such as shifts in supplier locations, production efficiency, or material compositions (Anthonissen et al., 2015; Yu et al., 2020). As a result, emission factors derived from these datasets can become outdated, and may not accurately represent current procurement activities, reducing the relevance of reported emissions. Furthermore, inconsistencies in impact assessment methodologies, such as the use of IPCC, ReCiPe, CML, TRACI, and other frameworks, lead to variations in reported environmental impacts, making comparisons across studies difficult.

IV.1.2 Inconsistencies in Standards

As various standards can be employed for the assessment of procurement emissions, differing requirements and recommendations lead to methodological inconsistencies between standards and consequently in our selected studies. As the OLCA and GHG Protocol standard are the most common standards in our selection, as seen in Figure 2-17, the discussion of methodological inconsistencies mainly focuses on these standards. The most prevalent inconsistencies include non-transparent methodological choices, divergent uses of the term "*hybrid"* for inventory approaches (i.e., data collection) combined with a different understanding of the bottom-up and top-down approach, as well as a significant contrast in the selection of system boundaries, leading to inconsistencies in reported emissions. The absence of harmonized standards complicates comparisons across industries and regions, making it difficult to benchmark procurement-related emissions effectively (Ozawa-Meida et al., 2013; Townsend and Barrett, 2015)

Among these standards, the GHG Protocol has become the most widely used in both corporate practice and institutional reporting, particularly in the private sector, due to its alignment with ESG frameworks, financial disclosure systems, and global initiatives such as the Science-Based Targets initiative (SBTi). Its strength lies in providing a mono-impact, organization-level accounting structure, which facilitates annual reporting, regulatory compliance, and the communication of long-term decarbonization ambitions. Conversely, OLCA adopts a multi-impacts and life-cycle-oriented perspective, which, although more granular, is less frequently adopted at the organizational level due to its complexity and data requirements.

A major inconsistency lies in the varying interpretation of hybrid approaches across standards. In GHG Protocol–based assessments, the top-down approach typically refers to the use of monetary data from

EEIO tables, while bottom-up refers to physical activity (Alvarez et al., 2014; Baddley and Rasheed, 2023; Herth and Blok, 2023; Keil, 2023). However, OLCA literature treats physical top-down data, such as aggregated procurement quantities, as top-down as well, even though the source is not monetary (ISO 14072, 2024; UNEP, 2015). The GHG Protocol does allow for hybridization of data sources (combining monetary and physical), but this flexibility often leads to inconsistencies in how the hybrid label is applied and interpreted, especially when studies fail to document allocation rules or the degree of primary versus secondary data use. Furthermore, aside from procurement emissions in Scope 3, some classify energy related data from Scope 2 as bottom-up inventories due to the physical units used (Baddley and Rasheed, 2023; Keil, 2023). However, without an allocation of energy flows to the product level, OLCA standards would define energy related data as top-down inventories (UNEP, 2015).

Further inconsistencies arise with the selection of system boundaries, which vary significantly between standards. OLCA studies adopt a product-focused perspective, typically using cradle-to-gate or cradle-to-grave boundaries, making them particularly suited for organizations with substantial upstream and downstream impacts from physical products. This approach allows for the identification of hotspots across the entire product life cycle, including procurement, providing a strong analytical basis for emission reduction strategies. In contrast, GHG Protocol studies use a broader organizational view, categorizing emissions into 15 predefined categories across Scopes 1, 2, and 3, including various supporting operations. While this enables a more comprehensive overview of emissions across an organization, it lacks the granularity required for detailed product-level assessments. Nevertheless, some OLCA studies mention Scopes and activity categories from the GHG Protocol to further differentiate organizational activities, as concepts from the GHG Protocol have influenced other methodologies and standards (de Camargo et al., 2019; Rimano et al., 2021).

This discrepancy becomes particularly problematic when applied to service providers, whose system boundaries under OLCA are often restricted to cradle-to-gate due to the absence of product-related downstream activities. However, service providers are directly responsible for the use and end-of-life phases of their purchased goods, such as office supplies, cleaning products or pharmaceuticals. Emissions from these activities occur within the organization itself, typically classified under energy consumption or waste generation. Consequently, although a case study from a service provider would be classified as cradle-to-gate without downstream activities, it inherently includes all required emissions from the use and end-of-life phases. However, since cradle-to-gate boundaries do not explicitly account for these downstream impacts, there is a potential risk of underreporting procurement-related emissions. While some organizations may deliberately exclude downstream impacts due to a lack of control over the use phase or disposal, this exclusion can still result in an

incomplete representation of the overall environmental footprint. Conversely, GHG Protocol system boundaries provide a broader coverage of all organizational activities but may overlook specific product life cycle emissions, making it challenging to conduct detailed product-level emission management.

IV.2 Quantifying Procurement Emissions and Data Inventory Approaches: Assessing Methodological Trade-offs and Goal Alignment

Given the complexity of supply chains, data limitations, and methodological challenges, achieving a comprehensive and accurate emission calculation at the organizational level often necessitates methodological trade-offs. While the selected case studies outline defined goals, the question arises as to whether the appropriate methods for emissions quantification or data inventories were selected to achieve those goals or if the described compromises hindered a coherent application. Figure 2-19 presents the total number of identified goals per category across the case studies, alongside their corresponding methods for emissions quantification and their procurement inventory approaches, highlighting that numerous studies pursue multiple goals, some of which extend beyond carbon emissions to cover broader environmental impacts.

IV.2.1 Goals Alignment with Data Inventory Approaches

Figure 2-19 highlights a disconnect between stated objectives, such as the identification of hotpots, the support for strategic decisions, the reduction of pressure on the environment, and the understanding of risks and impact reduction opportunities, important to enable reliable and impactful sustainability strategies, and the inventory approaches used to achieve them. Despite their importance, these goals are predominantly addressed with top-down monetary data, which lacks the granularity needed for process-level hotspot identification, effective decision-making, and therefore to understand reduction opportunities due to a lack of organization-specific information. Bottom-up physical data, the most accurate and suitable inventory approach for decarbonization strategies, is underrepresented in achieving these objectives. Instead, it is more commonly linked to tracking environmental performance, where the use of accurate data offers clear advantages, as well as with marketing objectives, where high-resolution data is not essential. Physical top-down data is frequently used for reducing environmental pressure, as it helps identify hotspots across product portfolios and procurement activities, yet it remains insufficient for detailed process-level interventions. For meaningful strategic decisions, reduction opportunities, and ultimately sustainable innovation through eco-design, hotspots identified with physical top-down data should still be analyzed with bottom-up physical data as an additional assessment on the process level.

Hybrid inventories based solely on physical data appear more suitable for impact reduction, as they allow for detailed bottom-up assessments when necessary. Ultimately, the overreliance on monetary

data limits the effectiveness of sustainability strategies, echoing concerns from the SBTi corporate survey (SBTi, 2024a). The lack of supplier-specific bottom-up data and high-quality emission factors forces reliance on EEIO and hybrid methods, which - while practical - may compromise the credibility and impact of disclosed sustainability goals. Addressing these limitations is essential to align methodological choices with meaningful decarbonization efforts.

The continued reliance on monetary data, despite its limited resolution, often reflects pragmatic constraints rather than methodological preference. In many case studies, particularly those conducted at the organizational level, companies face significant barriers in accessing bottom-up or supplier-specific data. This is often due to a lack of direct power over suppliers, especially in long or fragmented value chains, where environmental data is not contractually required or systematically shared. As a result, many assessments must proceed without the support of specific primary data. In this context, EEIO-based inventories are adopted out of necessity, not because they are ideal for guiding emission reduction strategies. Moreover, organizations are often under pressure to report quickly and regularly, driven by ESG frameworks, investor expectations, or internal carbon neutrality targets. These factors make monetary approaches attractive, as they can be implemented rapidly using existing procurement or financial records, even if they offer only a coarse approximation of actual impacts. Therefore, while these methods may fall short of delivering supplier-level insights or actionable reduction pathways, their use must be understood as a response to real-world constraints, rather than a dismissal of methodological rigor.

Hybrid approaches emerge as a pragmatic compromise, combining top-down and bottom-up inventories with both physical and monetary data to balance accuracy, scalability, and resource and time constraints. While these methods enhance hotspot identification and strategic decision-making, their effectiveness in driving actionable decarbonization strategies remains uncertain. Hybrid inventories based solely on physical data appear more suitable for impact reduction, as they allow for detailed bottom-up assessments when necessary. Overall, while the most commonly set goals are those related to sustainable innovation and decarbonization strategies, most applied inventory approaches linked with these goals are not or only partly suitable to effectively realize impactful reduction measures and strategies due to an overreliance on monetary data.

IV.2.2 Goals Alignment with Emission Quantification Methods

The alignment between case study goals and emission quantification methods is critical for ensuring robust and actionable sustainability strategies. Figure 2-19 illustrates the distribution of LCA, EEIO analysis, and hybrid approaches (EEIO & LCA) in relation to identified goals. The results highlight that while LCA remains the most frequently used method, particularly for hotspot identification and

strategic decision-making, the reliance on EEIO and hybrid methods raises concerns regarding the accuracy and granularity of emissions data.

Key sustainability goals such as hotspot identification, strategic decision-making, and reducing environmental pressure predominantly rely on LCA or hybrid methods, reflecting the need for process-level insights. However, EEIO, which provides aggregated, sector-level estimates, plays a substantial role in supporting high-level organizational decisions, despite its limitations in capturing supplier-specific and product-level variations. The reliance on EEIO without LCA for impact reduction opportunities and environmental performance tracking suggests a potential trade-off between data availability and methodological suitability.

Hybrid approaches are frequently used for complex assessments, particularly in cases where supply chain-wide emissions need to be estimated while maintaining some level of specificity. However, their effectiveness in guiding actionable reduction measures remains questionable if not supplemented with detailed process-level data.

Overall, while LCA and hybrid methods appear well-aligned with high-priority sustainability goals, the frequent use of EEIO alone for strategic decision-making and environmental tracking suggests a risk of oversimplified assessments. To ensure meaningful decarbonization strategies, organizations should prioritize hybrid models or LCA with stronger bottom-up integration, reducing overreliance on top-down EEIO estimates that may lack organization-specific resolution.

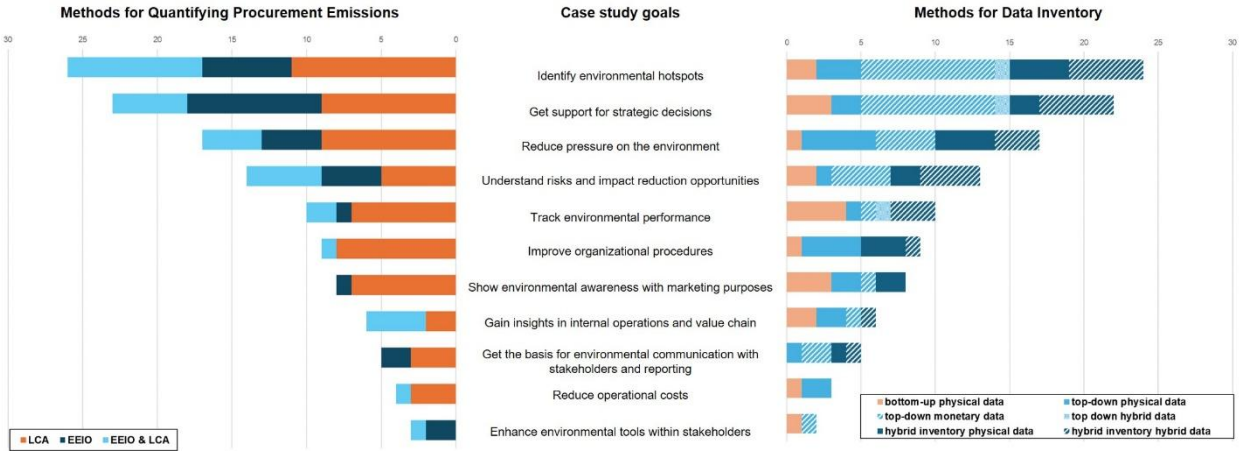


Figure 2-19 Linking Case Study Goals to Methods for Quantifying Procurement Emissions and Data Inventory Approaches

IV.3 Pathways for Harmonization

For a better integration and management of product-related and organizational activities, we propose a further distinction of Scopes and activity categories of the GHG Protocol based on concepts from Product LCA principles, as suggested by Aigner (2024). As shown in Figure 2-20, the product environmental accounting domain forms the foundation of organizational assessments.

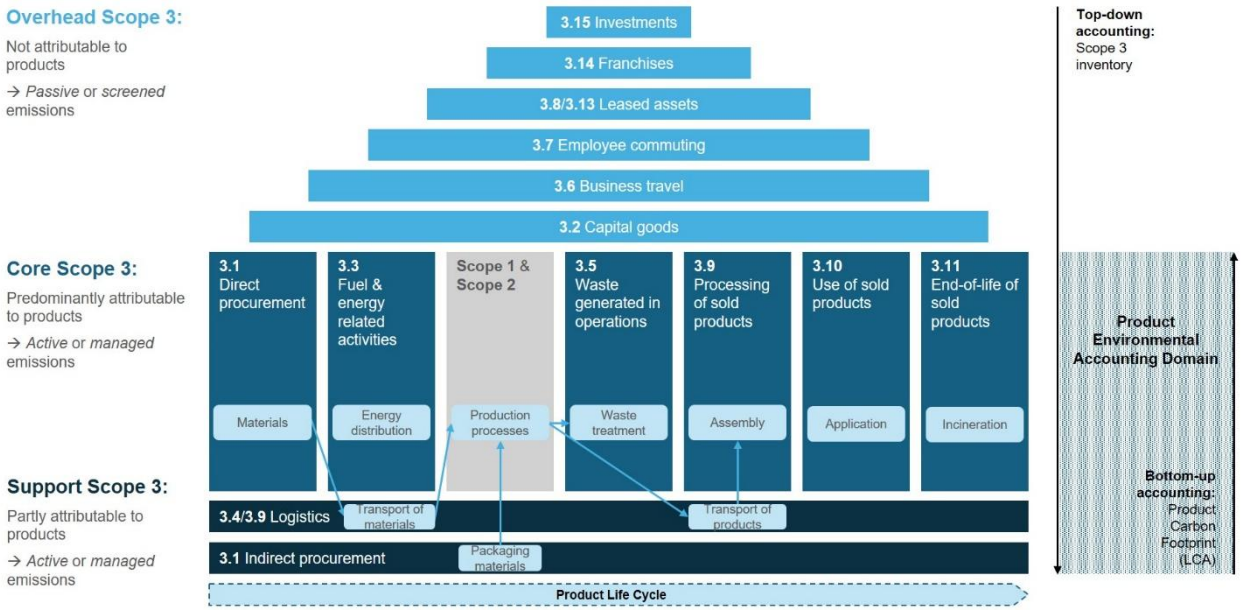


Figure 2-20 Integration of Organizational and Product-Related Activities (adapted from Aigner (2024))

Core activities are predominantly attributable to products. and include all processes relevant to the product's life cycles, such as direct and energy-related Scope 1 and 2 activities. Supporting activities, including logistics or indirect procurement like packaging materials, represent Scope 3 processes that are partially attributable to products. The product environmental accounting domain can be assessed with bottom-up data and LCA-methodologies, enabling a detailed analysis and management of emissions. In contrast, overhead activities on the organizational level include business travel, employee commuting or investments. These activities, classified as overhead Scope 3, are not attributable to products and present limited direct management opportunities. This structured differentiation of system boundaries enables organizations to prioritize emission reduction efforts, distinguishing *managed* or *active* activities with significant impacts and direct reduction opportunities (core and supporting activities), and *screened* or *passive* activities with indirect influence (overhead). Passive activities offer limited operational influence and, at best, indirect reduction opportunities (Aigner, 2024).

V. Conclusion

This study investigates the current state of methodologies for accounting Scope 3 procurement emissions. It focuses on the main methodological approaches like EEIO, LCA, and hybrid methods that combine both. The analysis includes data sources, standards, and system boundaries, providing a detailed evaluation of their application and discusses identified limitations and inconsistencies regarding data, methodological applications, and defined study goals. To ensure comprehensive insights, the review covers case studies across diverse industries, emphasizing methodological practices and their contextual relevance.

The literature analysis has helped to identify the main carbon accounting practices for the calculation of procurement emissions, highlighting their strengths and limitations. LCA provides granular, product-level insights but is resource-intensive and often constrained by data gaps. EEIO analysis offers a broader systemic perspective but lacks the granularity needed for detailed assessments. Hybrid approaches, which integrate the strengths of both LCA and EEIO data or bottom-up and top-down inventories, emerge as a promising solution to balance detail and coverage. However, significant challenges remain, including the availability and quality of supplier-specific data, dynamic and complex supply chains, and a lack of transparency in data and reporting practices. The reliance on generic databases and limited access to supplier-specific data undermines the accuracy of emission inventories.

While different hybrid approaches are commonly used, it is unclear whether they offer comparable possibilities for reducing carbon emissions as bottom-up approaches. Although the accurate tracking of emissions over multiple reporting periods is essential to follow emission reduction pathways, organizations additionally need reliable cost estimates for decarbonization measures. Economic efficiency calculations, such as the Life Cycle Costing (LCC) concept, could be integrated in supply chain carbon accounting practices for strategic emission reductions. These limitations highlight the need for further research on the applicability of hybrid approaches and LCC calculations to actual decarbonization measures for organizations.

As this review focuses on scientific literature, the representation of regions, sectors, methods, standards, and more may not reflect that of applications outside of academia. In addition, a broader range of applications, especially those found in grey literature or industry practice, could not be fully addressed here. Exploring such methods, as well as innovative combinations of existing models, lies beyond the scope of this review but represents an important avenue for future research.

Current standards, such as the GHG protocol, should be contextualized and re-evaluated according to identified methodological strengths and challenges, enabling the selection of appropriate methods for strategic decarbonization. In this context, differentiating between product-related and organizational-level activities can support a more targeted and harmonized approach to carbon accounting. The integration of product environmental accounting principles into organizational boundaries can help distinguish activities with high management potential (e.g., core and supporting activities) from those with limited reduction leverage (e.g., overhead Scope 3 categories). This conceptual refinement facilitates more informed prioritization of decarbonization strategies while enhancing methodological clarity. A detailed understanding is crucial to enhance the precision of carbon accounting, ensuring

more robust insights for decision-making. Without adaptations, these standards risk limiting their relevance and applicability to diverse organizational contexts.

To address these challenges, promoting collaboration between public or private organizations and suppliers is essential to improve the availability and reliability of primary data. This requires implementing new strategies that incentivize supplier transparency and fostering partnerships that enable robust data sharing. Expanding open-access emission databases could help standardize carbon accounting practices, ensuring greater consistency and accessibility of data across industries and regions. Advancing hybrid methodologies is also critical, leveraging emerging technologies such as artificial intelligence, blockchain, and internet of things enabled real-time monitoring to minimize human error, enhance data granularity, and improve consistency and data verification. Unified standards and approaches are necessary to resolve inconsistencies in methods, system boundaries, data types, and reporting frameworks, while greater transparency in studies will enable better comparability across research. Sector-specific studies should be conducted to address the unique challenges of various industries, and capacity-building initiatives must be encouraged to equip organizations with the skills and tools required for advanced carbon accounting. Innovative combinations of LCA and EEIO or bottom-up and top-down physical data, tailored to specific industries or organizational needs, can further enhance the precision and applicability of emissions accounting. Finally, organizations should adopt sustainable innovation as a core strategy, not just as compliance through reporting measures or voluntary carbon offsets, but as a competitive advantage, driving actual progress towards reducing their carbon footprints and contributing to global climate goals.

3| Strategic Roadmapping for Scope 3 Procurement Emissions: Insights from MICMAC and the Sustainability Balanced Scorecard

This chapter provides a strategic framework to improve the reliability of Scope 3 emissions accounting in procurement. It identifies key challenges through literature and expert analysis, categorizes them using the 6M framework, and maps their interdependencies with the MICMAC method. Based on these insights, it proposes a strategic roadmap using the Sustainability Balanced Scorecard (SBSC) to support more accurate, transparent, and actionable emissions reporting.

This chapter is adapted from the article "Improving Scope 3 Procurement Emissions Accounting: A Strategic Approach Using MICMAC and the Sustainability Balanced Scorecard", authored by Essouid et al., and currently under review (2nd round) in Corporate Social Responsibility and Environmental Management.

I. Introduction

Carbon accounting has become a foundational component of corporate sustainability strategies, with Scope 3 emissions, particularly those linked to procurement, emerging as one of the most complex and consequential challenges. Despite two decades of methodological refinement, the reliability of Scope 3 data remains problematic, especially when used to support strategic decision-making.

The introductory chapter and Chapter I established the theoretical and methodological context of this issue. The introduction highlighted the strategic and regulatory pressures shaping corporate decarbonization, emphasizing procurement as a key area of intervention. Chapter I reviewed the main Scope 3 accounting approaches, and revealed critical inconsistencies, limitations, and trade-offs in current Scope 3 practices.

Scope 3 emissions from purchased goods and services are deeply embedded in complex, multi-tiered supply chains. Their measurement is hindered by limited supplier data, inconsistent methodologies, and fragmented system boundaries. Despite increasing regulatory demands, such as the EU's Corporate Sustainability Reporting Directive (CSRD) and the SEC's climate disclosure requirements in the U.S., data reliability remains a persistent concern (European Commission, 2023a; Securities and Exchange Commission, 2024). Few studies have addressed this challenge through an integrated approach combining systemic analysis with strategic management tools.

Echoing Lord Kelvin's assertion (1891) that "If you cannot measure it, you cannot improve it", this

chapter argues that measurement without a clear understanding of structural barriers can lead to irrelevant data and ineffective decisions. Reliable emissions accounting must therefore go beyond technical precision to address the organizational and systemic factors that shape data quality and usability.

Against this background, this chapter aims to move from methodological review to actionable insight. It addresses the following research question:

How can the reliability of Scope 3 emission calculations related to procurement be improved to support more effective corporate sustainability decision-making?

This main question is broken down into three sub-questions:

1. What are the key factors influencing the reliability of Scope 3 emission calculations related to procurement?
2. How do these factors interact and influence each other in shaping Scope 3 data reliability?
3. What strategic roadmap can be proposed to improve Scope 3 emissions accounting and enhance corporate sustainability decision-making?

To address these questions, the study combines diagnostic and strategic tools to move from understanding challenges to designing an actionable strategic tool. It first identifies and presents the challenges of Scope 3 data reliability using the 6M framework, then examines their interdependencies through MICMAC structural analysis (an acronym for Cross-Impact Matrix Applied to Classification ("Matrice d'Impacts Croisés Multiplication Appliquée à un Classement" in French)), and finally reorganizes the results into a Sustainability Balanced Scorecard (SBSC) framework. This approach generates a structured and better-founded strategy map for managing the reliability of Scope 3 procurement emissions while strengthening coherence and accountability in corporate decarbonization.

The novelty of the study lies in its dual contribution: substantively, it deepens the understanding of the interdependent factors that undermine Scope 3 reliability and translates them into an improvement pathway; methodologically, it advances an integrated 6M–MICMAC–SBSC sequence that links diagnostic insight with strategic deployment, offering a replicable and adaptable model for addressing other complex sustainability.

This chapter is structured as follows. Section II outlines the methodological approach used to identify, categorize, and analyze the key factors affecting Scope 3 emissions data reliability in procurement. Section III presents the results of the study, including the identification of key challenges through literature review and expert survey analysis using NVivo software. These challenges are then classified

using the 6M framework, which provides a structured lens for classification. Additionally, the MICMAC structural analysis framework is applied to highlight the interdependencies among these categorized challenges. Finally, it proposes a strategic roadmap following the SBSC model to enhance the quality and robustness of Scope 3 emissions accounting. Section IV discusses the strategic implications for companies, policymakers, and researchers, along with the limitations of the study and directions for future research. Finally, Section V concludes with a summary of key findings, implications for corporate sustainability.

II. Materials & Methods

Evaluating Scope 3 emissions from procurement requires a clear and robust method, capable of addressing the diverse data sources, uncertainties, and interlinked factors that influence result accuracy. To this end, the present study adopts a three-step methodological approach that begins with the identification and categorization of key factors influencing the reliability of Scope 3 emissions in procurement, followed by a structural mapping of their interrelationships, and ultimately leads to the development of a strategic roadmap to guide targeted improvements (Figure 3-1). Specifically, five analytical tools guide the process:

Step 1,a. a systematic literature review using the PRISMA methodology to identify and screen relevant challenges from academic articles related to Scope 3 emissions in procurement (Page et al., 2021);

Step 1,b. an elaborative content analysis supported by NVivo software to extract, code, and synthesize the expert survey responses related to Scope 3 emissions challenges (Jenny, 1997; Lejeune, 2017);

Step 1,c. the 6M framework for the systemic classification of influencing variables across six domains (Gijo and Scaria, 2010; Imai, 1986);

Step 2. structural mapping using the MICMAC methodology, as applied in the earlier study, to identify, organize, and analyze influence–dependence relationships among the challenges (Bertalanffy, 1968; Godet, 2007; Wiener, 1948);

Step 3. the Sustainability Balanced Scorecard (SBSC) to translate findings into strategic priorities and decisions (Figge et al., 2002; Kaplan and Norton, 1996).

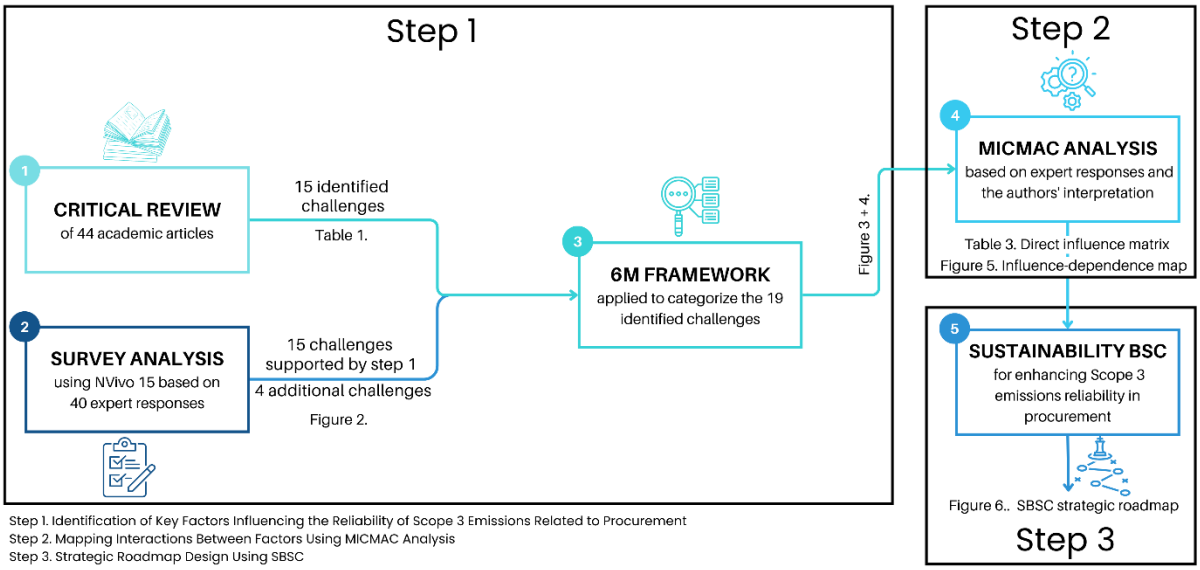


Figure 3-1 Research Methodology Overview

II.1 Identification of Key Factors Influencing the Reliability of Scope 3 Emissions Related to Procurement

To address the first sub-question, this study uses three analytical tools to identify the principal challenges limiting the reliability of Scope 3 emissions data related to procurement. This step integrates evidence from a systematic literature review and a qualitative expert survey, followed by the application of the 6M framework to structure and categorize the identified challenges. Together, these methods ensure both conceptual breadth and practical relevance.

II.1.1 Systematic Literature Review

As outlined in Section 2.B.II, a systematic review following the PRISMA methodology (Page et al., 2021) was used to identify relevant peer-reviewed literature on Scope 3 emissions. Building on that review, this section analyses the 44 selected articles to identify the critical challenges affecting the reliability of Scope 3 emissions calculations (cf. details of the screening process in Figure 2-13).

II.1.2 Expert Survey

To complement the literature findings, a qualitative expert survey was conducted to capture experiential insights from professionals involved in Scope 3 emissions accounting and procurement.

Sampling and Inclusion Criteria

The aim was not statistical generalization, but rather to generate in-depth understanding of practitioner perspectives, validate literature-based challenges, and reveal additional emergent themes relevant to data reliability. Participants were selected through non-probabilistic and purposive sampling (Campbell et al., 2020; Guest et al., 2006) to ensure diversity in professional roles and sectoral representation. Inclusion criteria required respondents to:

1. Possess professional experience in GHG accounting, sustainable procurement, or related fields;

2. Hold an active role in decision-making, data management, or sustainability reporting processes; and

3. Demonstrate familiarity with Scope 3 accounting practices, either through direct implementation or advisory experience.

Recruitment took place between January and April 2025 through LinkedIn, professional networks, email invitations, and targeted outreach at sustainability and procurement events, including Sustainability LIVE: Net Zero and Procurement & Supply Chain Live: Sustainability, held in London in March 2025. In total, 40 complete responses were obtained and retained for analysis; 3 partial or ambiguous submissions were excluded. This sample size is considered appropriate for qualitative expert inquiry, particularly within a grounded theory context (Glaser & Strauss, 1967), where the aim is to ensure comprehensive thematic coverage rather than statistical representativeness. Prior methodological guidance supports this range: Creswell (1998) recommends 20–30 interviews for grounded theory studies, Kuzel (1992) suggests 12–20 for heterogeneous samples, and Bertaux (1981) identifies 15 as the smallest acceptable qualitative sample. Accordingly, the 40 expert responses in this study provide a robust basis for analytical depth and ensure both data richness and diversity of perspectives.

Respondents represented organizations across manufacturing, services, consulting, and public administration sectors and were grouped into four professional categories to ensure representativeness: (A) Sustainability professionals (42.5%): Experts in GHG management, LCA, and environmental data analytics ; (B) Procurement specialists (27.5%): Professionals in supply chain management and sourcing ; (C) Hybrid-role professionals (17.5%): Those working at the intersection of sustainability and procurement ; (D) Other actors (12.5%): Including data scientists, and policy analysts.

Most respondents were senior, with 42.5% reporting 5–10 years of experience, and 37.5% over 10 years. Only 20% had less than five years, reinforcing the credibility and depth of insights collected.

Data Sources and Survey Design

The survey (Appendix 3-1) combined closed- and open-ended questions across five sections: (1) an introduction outlining the study's purpose; (2) respondent background information (e.g., role, field, and years of experience); (3) open-ended items on reliability challenges, influencing factors, and improvement opportunities; (4) a Likert-scale section rating the perceived importance of identified challenges (1 = very low, 5 = very high); and (5) a final section for additional comments or examples

from practice. This structure enabled the collection of both quantitative and qualitative insights into the reliability of Scope 3 emission data.

The qualitative dataset consisted of 40 complete, well-articulated responses to the open-ended questions, forming a rich and diverse corpus of narrative data. Closed-ended responses were also analyzed within NVivo to align narrative feedback with quantitative ratings. Survey data were further analyzed by respondent role and years of experience to assess how perceptions varied across stakeholder groups.

Qualitative Content Analysis and Coding Procedure

Data were analyzed using NVivo 15, a qualitative data analysis software (Jenny, 1997; Lejeune, 2017; Seror, 2005). A hybrid coding approach was applied, combining deductive coding derived from the literature review (e.g., data quality, supplier engagement, methodological alignment) with inductive coding that allowed new, practice-based themes to emerge from the text (e.g., transparency, software capabilities, automation). This approach aligns with elaborative coding principles outlined by Saldana (2021) and supports iterative refinement of analytical categories. Text segments, typically phrases or short sentences, were treated as the primary coding units in NVivo to ensure consistency and comparability across responses.

An initial set of 25 themes emerged from the qualitative coding process, reflecting the diverse challenges identified by respondents. These themes were then compared and aligned with 15 literature-derived challenges, allowing for conceptual integration between empirical insights and established research. Through this iterative comparison, four additional challenges were identified that were not explicitly discussed in the existing literature but were strongly supported by practitioner evidence. The process involved three stages: (1) open coding, where textual segments were tagged with preliminary labels; (2) axial coding, where related codes were grouped into broader conceptual categories; and (3) selective coding, where the most salient themes were consolidated and refined to form the final set of challenges.

Each theme was evaluated for both frequency of occurrence and conceptual significance, ensuring that the final challenges reflected the most relevant practitioner and methodological issues. A challenge was retained if it was mentioned by at least 10% of respondents or consistently supported by the literature, ensuring both empirical and theoretical validity.

Memo-writing and code comparison functions in NVivo were used to document coding decisions and maintain consistency, and data were reanalyzed after codebook stabilization to confirm thematic coherence. To strengthen analytic rigor, a random subset of responses (20%) was re-coded by a second

research assistant after two weeks, yielding a high consistency rate (Cohen's κ = 0.93). The resulting 19 challenges provide an integrated insight linking academic knowledge with real-world experience and serve as the empirical foundation for the MICMAC structural analysis.

Closed-Ended Rating and Experience Weighting

The survey included closed-ended ratings of challenge importance on a Likert-scale. Following common practice in management and sustainability research, these responses were analyzed as approximately interval to compute weighted factors.

In Multi-Criteria Decision-Making (MCDM) terms (Chakraborty et al., 2024), we applied a weighting model with a single criterion "seniority", to reflect the level of professional experience of respondents. We operationalized seniority via band midpoints (direct-rating scheme), treating the top-coded band ">10 years" as 10–30 years (Table 3-1).

Table 3-1 Seniority Weighting Scheme For Expert Ratings

Experience range	Minimum experience	Maximum experience	Weighting factor
0 – 2 years	0	2	1
2 – 5 years	2	5	3.5
5 – 10 years	5	10	7.5
> 10 years	10	30	20

Let r_{jm} be the rating by respondent j for challenge m, and w_j the seniority weight. The weighted score for challenge m is : $\bar{r}_m{}^{(w)} = \frac{\sum_{j=1}^{N} r_{jm} \times w_j}{\sum_{j=1}^{N} w_j}$. Practically, each rating was multiplied by its seniority weight ($rw_{jm} = r_{jm} \times w_j$) prior to aggregation. This weighting yields a more nuanced estimate of perceived importance by accounting for expertise while retaining scale interpretability.

II.1.3 Classification of Challenges Using the 6M Framework

To organize and interpret the identified challenges in a structured manner, the study applied the 6M framework, a diagnostic tool originating from industrial quality management (Gijo and Scaria, 2010; Imai, 1986). The framework classifies influencing factors into six key categories, providing a comprehensive lens to analyze the root causes affecting the reliability of Scope 3 emissions in procurement contexts:

- Man: human competencies, stakeholder collaboration, and behavioral drivers;
- Method: protocols, procedures, and methodological harmonization;
- Material: quality, granularity, and origin of input data;
- Machine: availability and integration of digital infrastructure and software tools;
- Measurement: the use of standardized indicators, emission factors, and metrics;

- Management: organizational policies, governance structures, and leadership engagement.

Each challenge identified from the literature review and expert survey was assigned to one of these categories. The use of the 6M framework not only supports structured problem-solving but also reflects a broader commitment to continuous improvement, a principle deeply rooted in industrial quality practices (McLean, 2019). This logic aligns with Life Cycle Management (LCM), which promotes continuous environmental, social, and economic improvement across the value chain, by identifying and addressing systemic barriers to sustainability (Sonnemann and Margni, 2015). This classification provided the analytical foundation for the next step: mapping the interdependencies among these challenges using the MICMAC method.

II.2 Mapping Interactions Between Factors Using MICMAC Analysis

The second sub-question is designed to explore how the previously identified factors interact within the broader system of Scope 3 emissions accounting in procurement. To address this, the study applied structural analysis operationalized through MICMAC method (Godet, 2007), within a systems-theoretic and cybernetic perspective (Bertalanffy, 1968; Wiener, 1948). Structural analysis identifies variables that are both influential and dependent within a system. In this study, it was used to build a conceptual model of reliability challenge interrelationships. MICMAC has been increasingly used in sustainability research including studies on green entrepreneurship in circular-economy contexts (Soleimani et al., 2023), digital empowerment for environmental sustainability (Salamzadeh et al., 2025), and water and wastewater management (Nazlabadi et al., 2023). These applications illustrate the method's capacity to map causal relationships in complex socio-environmental systems.

Data Sources and Matrix Construction

To operationalize this model, MICMAC method was employed to build an influence-dependence matrix, quantifying direct and indirect relationships. Binary values (1 = influence; 0 = no influence) indicate a direct relationship between two variables.

The interaction between any two factors is directional: if x influences y, this is denoted as 1 in cell (x, y), meaning x affects y, and y is dependent on x. This does not necessarily imply reciprocity, as the reverse relationship (y influencing x) may or may not exist. Thus, the matrix is asymmetric, and influence is not always mutual. The sum of values across a row represents influence exerted by that factor on others, while the sum of values down a column indicates its dependence.

The construction of the direct influence matrix was informed by three complementary sources: (1) the systematic literature review, which provided theoretical causal pathways; (2) the expert survey, which revealed practitioner-based cause–effect relationships derived from NVivo axial coding; and (3) the

authors' interpretive synthesis, linking both empirical and conceptual evidence. Based on these inputs, a preliminary matrix was drafted to capture the most frequently co-occurring and causally expressed relationships in the expert narratives. For instance, experts emphasized that insufficient training weakens communication and supplier data-sharing, establishing a directional link from "Training" to "Communication and Data Sharing" . Similarly, automation and digital integration were identified as enablers for reducing manual data errors, creating a link from "Automation and Real-Time Tracking" to "Manual Data Entry and Human Errors".

Expert Validation Process

To enhance transparency and reliability, the preliminary influence–dependence matrix was validated through an external expert consultation. A panel of five validators was convened to review and refine the proposed directional relationships. Their profiles reflect a diversity of experience across academia, public administration, and industry: (1) Sustainability procurement manager with seven years of experience in a government-owned company; (2) CEO of a start-up specializing in Scope 3 reporting (over ten years of experience); (3) Retired professor of procurement management with more than thirty years of academic experience; (4) Associate professor in sustainability management; and (5) Researcher in corporate decarbonization and climate data systems (over five years of experience).

Each validator was provided with the preliminary matrix and asked to assess the presence and direction of influence between variable pairs using binary scoring. Divergent opinions were discussed individually, and revisions were made until consensus was achieved. A research assistant independently cross-checked the final version against the literature to ensure alignment with established causal mechanisms and empirical evidence.

This validation process ensures that the matrix is not solely an authorial interpretation but a consensus-based synthesis of empirical data, expert judgment, and theoretical grounding. It enhances the methodological credibility of the MICMAC results and responds to calls for greater transparency in structural mapping exercises (Dhirasasna & Sahin, 2019).

Matrix Processing and Factor Classification

Following expert validation, the finalized direct influence matrix was processed through successive matrix multiplications to capture indirect and cumulative relationships. This iterative process, implemented via a Python-based computational script, stabilized the influence–dependence values at the third power (M^3), revealing both explicit and latent interactions among variables. The resulting coordinates allowed the classification of the challenges into five categories: (1*) Driver variables*: high influence and low dependence; (2) *Dependent variables*: low influence and high dependence; (3)

Linkage variables: high influence and dependence; (4) *Autonomous variables*: weakly connected to the system; (5) *Peloton variables*: moderately influential and dependent, positioned near the center of the influence–dependence map, playing transitional roles.

This typology offers a valuable lens for identifying leverage points and prioritizing intervention areas (Salamzadeh et al., 2024). For example, acting on driver variables can have cascading effects throughout the system, whereas linkage variables require careful monitoring due to their central, often unstable role.

II.3 Strategic Roadmap Design Using Sustainability Balanced Scorecard

To address the third sub-question, a strategy map was developed using the SBSC framework (Figge et al., 2002; Kaplan & Norton, 1996). Informed by MICMAC analysis, literature, and expert input, the SBSC served as a tool to translate a complex system of interrelated challenges, classified as driver, linkage, dependent, autonomous, and peloton variables, into a visual strategic tool showing priorities. As an extension of the traditional Balanced Scorecard, the SBSC integrates environmental and social objectives into performance management, aligning organizational strategy with sustainability goals.

SBSC Perspectives and Roadmap Structure

The obtained roadmap is organized across six, mutually reinforcing perspectives:

(1) Learning and Growth: addressing capacity-building, training, and digital capability gaps;
(2) Methodological: promoting harmonized accounting practices and improved data accuracy, *(this perspective is contextually included under the SBSC's flexible design and is not part of the canonical set).*
(3) Internal Process: embedding carbon metrics into procurement and governance structures;
(4) Stakeholder and Supplier: enhancing collaboration, data sharing, and transparency;
(5) Sustainability: aligning procurement with long-term environmental performance objectives;
(6) Financial: mobilizing resources, incentives, and investment to support decarbonization.

MICMAC → SBSC Translation Protocol

To ensure methodological transparency and replicability, we apply a rule-based protocol that preserves the causal structure uncovered by MICMAC. The perspective mapping by role illustrated in Figure 3-2 translates MICMAC roles to SBSC perspectives, following the approach of Trébucq et al. (2023). While the classification adopted in this study primarily follows the structure below, the relative positioning of perspectives may vary across sectors depending on contextual interdependencies and organizational maturity:

- *Driver* → Leadership (bottom axis). Aligned with the Learning & Growth perspective, this layer comprises leadership-driven enablers, strategic intent, communication, and capability development, that build the cognitive and data infrastructure required to activate higher-order processes.
- *Linkage* → Orchestration and deployment (intermediate axis). Corresponding to the Methodological, Internal Process, and Stakeholder & Supplier perspectives, this layer translates enablers into coordinated execution, operationalizing alignment and cross-boundary collaboration where interdependencies are most pronounced.
- *Dependent* → Outcomes (top axis). Reflecting the Sustainability and Financial perspectives, this layer consolidates and measures results, showing how leadership foundations and orchestration mechanisms materialize as reliability, impact, and risk-adjusted performance.
- *Autonomous & Peloton* → Context-responsive placement. Autonomous items are monitored as peripheral signals and linked to perspectives when context elevates their relevance; peloton items are managed as an interdependent bundle with joint objectives, shared KPIs, and shared accountability to ensure coordinated delivery.

The vertical ordering reflects systemic leverage revealed by MICMAC: drivers have high influence and therefore form the base; linkage items both influence and depend on others, so they sit at the orchestration layer; dependents have low influence and capture outcome performance at the top. The emphasis and sequence of perspectives are not fixed, they are calibrated by the MICMAC results, expert-elicited importance weights, so that the roadmap prioritizes what the structure and the experts indicate will move the system most, and company priorities (i.e., the organization's strategic objectives, regulatory commitments, risk appetite, and resource constraints).

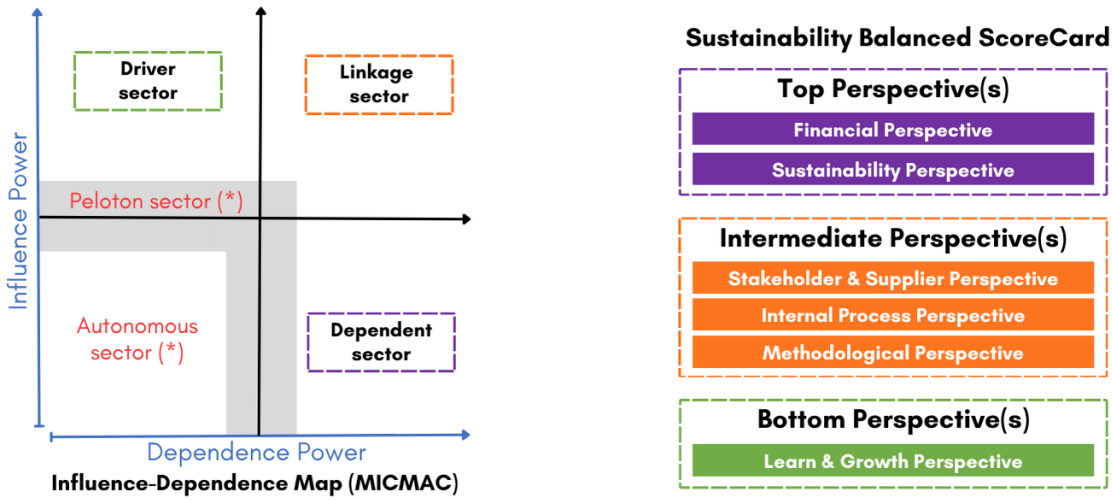


Figure 3-2 Role-based Translation of MICMAC Sectors Into the SBSC

A single variable may legitimately connect to one or more perspectives (primary and, where warranted, secondary links), reflecting its multi-layered managerial relevance. For clearer application, each selected perspective should specify (a) the strategic objective (what to achieve), (b) key actions (how to act), and (c) the expected impact.

This protocol is transferable with adaptation: for new Scope 3 categories or contexts, variables are re-elicited, MICMAC roles recalculated, and the same mapping rules applied to produce a category-specific SBSC while preserving methodological continuity. It offers a coherent, adaptable, and replicable bridge from structural diagnosis to strategic action, strengthening the reliability and integrity of Scope 3 reporting.

III. Results

This section outlines the study's key findings, following the three methodological steps: identification of Scope 3 emissions challenges (III.1), analysis of their interdependencies using MICMAC (III.2), and development of a strategic roadmap via the SBSC framework (III.3).

III.1 Literature Review and Expert Input Identify 19 Key Challenges to Scope 3 Emissions Accounting

III.1.1 Identification of Key Challenges from Literature

A structured review of the literature reveals a wide range of challenges compromising the reliability of Scope 3 emissions calculations in procurement. These challenges span technical, methodological, organizational, and human factors. Key issues include limited supplier engagement, inadequate communication and data-sharing, and a general lack of expertise in sustainability and carbon accounting. Manual data entry and persistent knowledge gaps further undermine coordination and data accuracy (Forin et al., 2019; Marx et al., 2020).

Methodological inconsistencies across suppliers, stemming from varying emission factors, reporting frameworks, and accounting practices, hinder data comparability. The complexity of emissions modeling and the widespread use of spend-based estimates based on aggregated financial data reduce methodological robustness (Cerutti et al., 2018; Chen et al., 2023).

Data-related challenges include low quality, insufficient granularity, and inconsistent or outdated datasets, which introduce significant uncertainty into emissions calculations (Cucchi et al., 2023; Forin et al., 2017).

Technological barriers also persist. Poor integration of procurement and emissions tracking systems, limited automation, and the continued reliance on spreadsheets restrict timely, scalable, and accurate data processing (Herth and Blok, 2023; Ozawa-Meida et al., 2013).

Other issues involve inconsistent data collection, lack of verification mechanisms, and poor alignment

with industry standards, affecting the traceability and credibility of reported emissions (Alvarez et al., 2014; Toniolo et al., 2023).

Finally, governance-related constraints, such as weak oversight, unclear policies, and limited resources, delay the integration of sustainability into procurement strategies (Anthonissen et al., 2015; Cimprich et al., 2019).

These recurring and interrelated challenges are synthesized in Table 3-2, with further details provided in Appendix 3-2.

III.1.2 Insights from Expert Survey

The expert survey (40 responses) confirmed the 15 challenges identified in the literature and revealed four additional, emergent issues not yet widely addressed in academic research on Scope 3 emissions in procurement. These insights were identified through qualitative coding and supported by the frequency of mentions across participant responses. Illustrative expert quotes (Table 3-3) highlight recurring issues such as communication barriers, data inconsistencies, and fragmented strategies.

Challenges marked with (*) indicate issues identified exclusively through expert survey responses, revealing four additional themes not yet widely addressed in the literature: (1) technological gaps in automation, AI, and real-time tracking of dynamic emissions data; (2) limited software capabilities for processing and integrating emissions information; (3) weak alignment between procurement practices and sustainability objectives; and (4) persistent transparency and visibility gaps across supply tiers.

Beyond these emerging issues, content analysis using NVivo 15 quantified the frequency of challenge mentions across professional groups, revealing clear patterns in emphasis and perception. Standardization and regulatory alignment (85%) emerged as the most frequently cited challenge, followed by expertise and knowledge gaps (75%), data-related issues (70%), automation and real-time tracking (53%), and procurement platform integration (50%). Figure 3-3 illustrates the distribution of these challenges by respondent category, enabling comparisons across professional backgrounds.

Table 3-2. Key Challenges Affecting the Reliability of Scope 3 Emissions in Procurement

Challenges		References
Communication and Data Sharing		*(Marx et al., 2020; Stenzel & Waichman, 2023)*
Supplier Readiness, Trust, and Cooperation		*(Alejandrino et al., 2022; Stridsland, Biørnstad, et al., 2023)*
Expertise, Training, Knowledge Gaps and Understanding		*(Forin et al., 2019; Stridsland, Stounbjerg, et al., 2023)*
Manual Data Entry and Matching, and Human Errors		*(Herth & Blok, 2023; Ozawa-Meida et al., 2013; Paepe et al., 2023; Stridsland, Stounbjerg, et al., 2023)*
Inconsistent Supplier Methodologies		*(Alejandrino et al., 2022; Lo-Iacono-Ferreira et al., 2017; Montoya-Torres et al., 2015)*
Methodologies and Emissions Calculations		*(Mähönen et al., 2023; Vieira et al., 2024)*
Data Aggregation from the Use of the Spend-Based Approach		*(Cucchi et al., 2023; Finogenova et al., 2019; Forin et al., 2017; Martinez et al., 2019; Resta et al., 2016; Stridsland, Stounbjerg, et al., 2023; Toniolo et al., 2023; Townsend & Barrett, 2015; Wiedmann et al., 2009)*
Supplier Data Quality and Consistency		*(Forin et al., 2017; Stridsland, Stounbjerg, et al., 2023)*
Challenges in Data	Data Completeness and Gaps	*(Baddley & Rasheed, 2023; Cerutti et al., 2018; Cimprich & Young, 2023; Cucchi et al., 2023; Demeter et al., 2021; Forin et al., 2017, 2019; Harasymchuk et al., 2024; Herth & Blok, 2022; Jungbluth et al., 2016; Keil, 2023; Lee & Cheong, 2011; Manzardo et al., 2018; Martinez et al., 2018; Montoya-Torres et al., 2015; Notarnicola et al., 2023; Pelton & Smith, 2015; Yu et al., 2020)*
	Data Consistency	
	Data Granularity	
	Data Quality and Precision	
	Use of Outdated Data	
Procurement Platform Integration for Carbon Accounting		*(Alejandrino et al., 2022; Bueno et al., 2022; Cerutti et al., 2018; Yu et al., 2020)*
Data Collection		*(Alejandrino et al., 2022; Alvarez et al., 2014; Forin et al., 2017; Lo-Iacono-Ferreira et al., 2017; Marx et al., 2020; Nordman et al., 2024; Ozawa-Meida et al., 2013; Toniolo et al., 2023)*
Data Verification		*(Ozawa-Meida et al., 2013)*
Standardization and Regulatory Alignment		*(Alvarez et al., 2014; Anthonissen et al., 2015; Chen et al., 2023; de Camargo et al., 2019; Forin et al., 2017; Georgiou et al., 2019; Gómez et al., 2016; Lee & Cheong, 2011; Neppach et al., 2017; Rimano et al., 2021)*
Weak Governance and Unclear Policies		*(Anthonissen et al., 2015; Cerutti et al., 2018; de Camargo et al., 2019; Kjaer et al., 2015; Yu et al., 2020)*
Cost, Time, and Resource Constraints		*(Cimprich & Young, 2023; Georgiou et al., 2019; Herth & Blok, 2022; Neppach et al., 2017)*

Table 3-3 Expert Survey Insights and Illustrative Quotes on Confirmed and Emerging Challenges

	Challenge	Illustrative Quote
C01	Communication and Data Sharing	*I-10 "Miscommunication impact reliability"* *I-5 "struggles in data sharing"*
C02	Supplier Readiness, Trust, and Cooperation	*I-5 "some are not willing to share information due to fear influences of business"*
C03	Expertise, Training, Knowledge Gaps and Understanding	*I-16 "Lack of expertise, knowledge gaps, limited training."*
C04	Manual Data Entry and Matching, and Human Errors	*I-19 "Manual data handling reduce accuracy"* *I-27 "Making manual data entry prone to errors"*
C05	Inconsistent Supplier Methodologies	*I-29 "Lack of a consistent emissions calculation approach among suppliers creates discrepancies"*
C06	Methodologies and Emissions Calculations	*I-37 "Current Scope 3 methodologies do not account well for factors like empty miles and fuel mix variations"*
C07	Data Aggregation from the Use of the Spend-Based Approach	*I-25 "Data is often too aggregated, making it difficult to assess specific supplier impacts"*
C08	Supplier Data Quality and Consistency	*I-12 "Supplier data is often incomplete, outdated, or inconsistent"*
C09	Challenges in Data	*I-2 "data gaps … key challenges include data quality, completeness and accuracy"* *I-18 "Inconsistent formats… outdated data…lack of granularity"*
C10	Procurement Platform Integration for Carbon Accounting	*I-22 "Current procurement platforms lack built-in carbon tracking"*
C11*	Automation, AI, and Real-Time Data Tracking	*I-14 "AI-driven tools with real-time data synchronization should be prioritized"*
C12*	Software Capabilities for Emissions Data Processing	*I-36 "Many companies lack the software capabilities to process complex emissions data"*
C13	Data Collection	*I-23 "…inconsistent data collection"*
C14	Data Verification	*I-7 "verification challenges hinder reliability"*
C15	Standardization and Regulatory Alignment	*I-31 "There is a lack of standardization across industries, making comparisons difficult"*
C16	Weak Governance and Unclear Policies	*I-19 "Lack of clear policies and enforcement weakens data governance"*
C17	Cost, Time, and Resource Constraints	*I-26 "Procurement teams often lack time and resources to focus on emissions tracking"*
C18*	Aligning Procurement with Sustainability Goals	*I-12 "Procurement strategies often lack alignment with sustainability goals"*
C19*	Supplier's lack of transparency	*I-20 "Limited supplier transparency"*

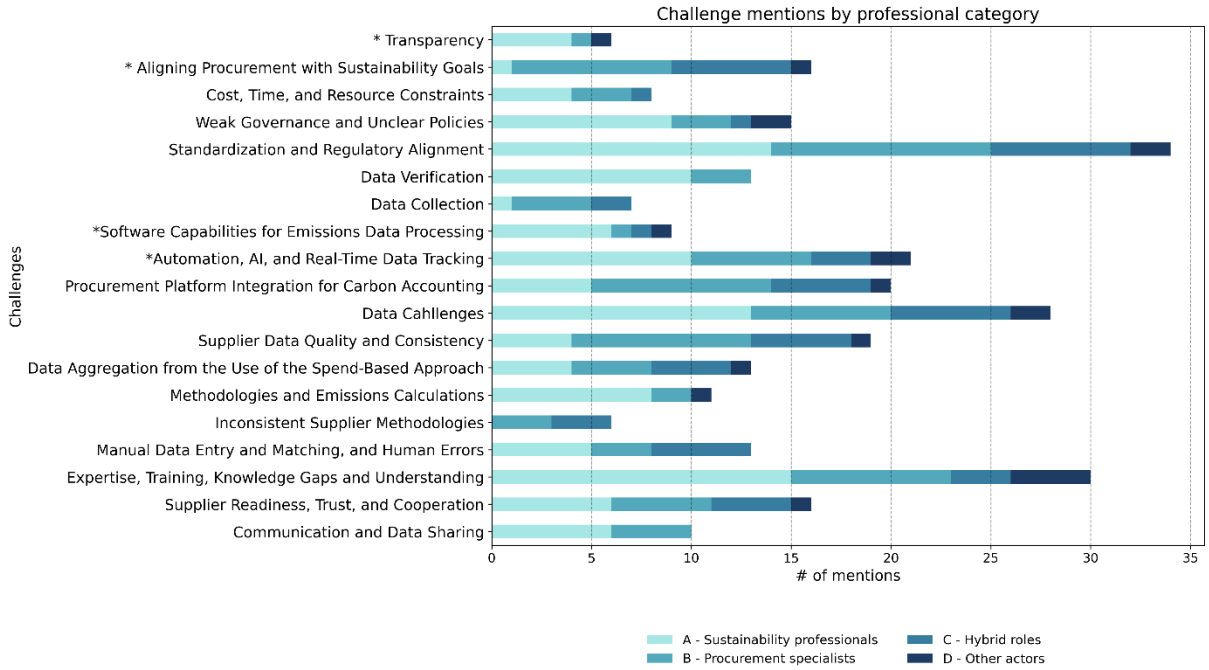


Figure 3-3 Challenge Mentions by Professional Category

Disaggregated analysis shows that sustainability professionals (A) prioritized knowledge and training gaps (88%) and regulatory alignment (82%), alongside concerns about data quality (76%), automation, and verification (59% each). Procurement specialists (B) unanimously cited regulatory alignment (100%) as their top concern, also emphasizing platform integration (82%), supplier data consistency (82%), and alignment with sustainability goals (73%). Hybrid-role professionals (C) similarly stressed regulatory alignment (100%) and sustainability goal integration (86%), frequently mentioning supplier cooperation (57%), data-related concerns (86%), and the limitations of spend-based approaches (71%). Other actors, including data scientists and policy analysts (D), most often highlighted expertise gaps (80%) and standardization (40%), data gaps (40%) or technological constraints (40%).

Overall, the findings align closely with prior literature (Finogenova et al., 2019; Forin et al., 2019; Martinez et al., 2019), confirming persistent barriers such as communication breakdowns, data inconsistency, methodological fragmentation, and limited supplier cooperation. At the same time, experts reaffirmed the growing urgency of addressing digitalization gaps, verification issues, and software limitations. Collectively, the results demonstrate that perceptions of key Scope 3 challenges are shaped by professional background, underscoring the need for cross-functional coordination.

III.1.3 Challenges Classification Using the 6M Framework

To structure the wide array of challenges identified through the literature and expert survey, the 6M framework was applied. The resulting classification is illustrated in Figure 3-4 using an Ishikawa diagram, highlighting the distribution of factors affecting the reliability of Scope 3 emissions in procurement.

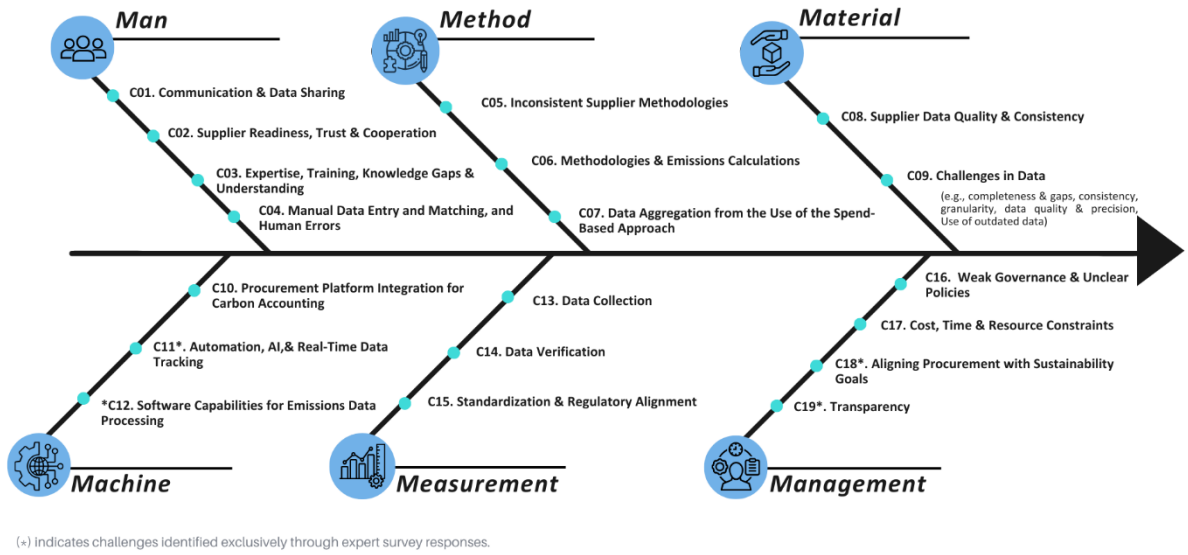


Figure 3-4 Ishikawa Diagram of Challenges Affecting the Reliability of Scope 3 Emissions in Procurement (Structured by the 6M Framework and Informed by Literature and Expert Survey)

The use of experience-based weighting enhances the robustness of the findings by giving proportionally greater influence to the perspectives of seasoned professionals. Table 3-4 presents the aggregated weightings for each of the 6M categories, derived from Likert-scale ratings and adjusted for experience (more details in Appendix 3-3). This approach enables a more nuanced interpretation of challenge importance across domains.

Table 3-4 Weighted Average Importance of 6M Categories Based on Expert Ratings and Experience-Adjusted Weighting

6M Category	Weighting factor
Man	3,94
Method	4,57
Material	4,64
Machine	3,35
Measurement	4,41
Management	4,51

The results indicate that Material and Method are perceived as the most critical categories influencing the reliability of Scope 3 emissions data, especially among highly experienced respondents. These findings underscore the importance of data quality and methodological rigor. Management and Measurement also ranked highly, pointing to the influence of internal governance and verification processes. Man, relating to human capabilities and skills, held moderate importance, while Machine was rated lowest, possibly indicating that technical infrastructure is not viewed as the primary bottleneck in emissions accounting.

To further explore how perceptions vary by professional background, challenge mentions were disaggregated by respondent group and visualized in a heatmap (Figure 3-5). The heatmap reflects the relative frequency of each challenge across the four professional categories: sustainability

professionals, procurement specialists, hybrid-role professionals, and other actors. Each cell represents the proportion of respondents in a given group who mentioned a particular challenge, thereby allowing for normalized comparison across groups of different sizes.

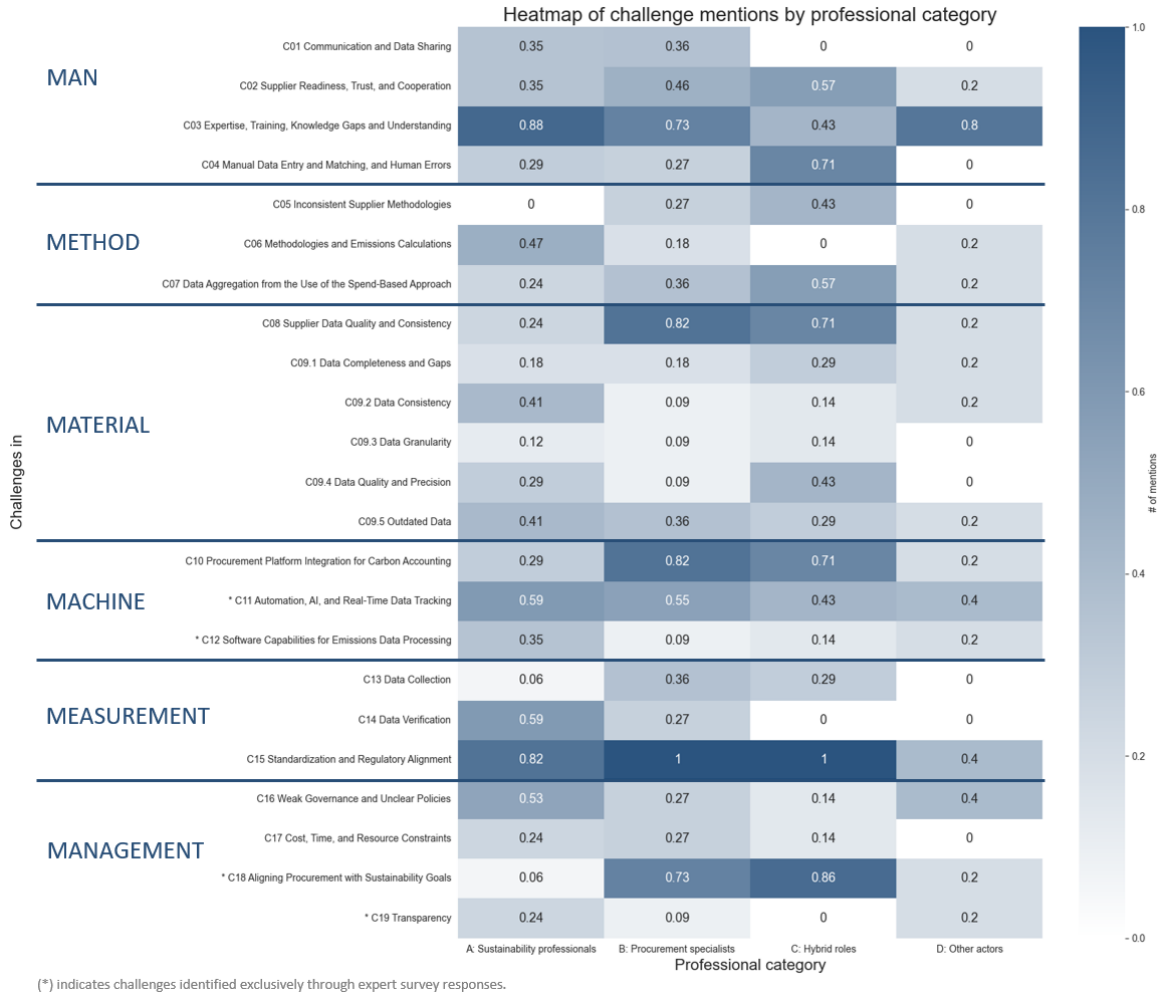


Figure 3-5 Heatmap of Challenge Mentions by Professional Category

This visual analysis reveals important differences in how various professional communities perceive and prioritize Scope 3 challenges. It also highlights the value of cross-functional perspectives in understanding and addressing the complexity of emissions reporting within procurement contexts.

III.2 MICMAC Structural Analysis Reveals Influence–Dependence Dynamics Among Scope 3 Emission Factors

To analyze how challenges in Scope 3 emissions accounting interact, a structural analysis was conducted using the MICMAC methodology (Godet, 2007). This method maps influence–dependence relationships among the 19 challenges identified through the literature review and expert survey, highlighting their roles as drivers, dependents, linkages, autonomous, or peloton elements. The analysis aims to uncover systemic dynamics that shape barriers and enablers in Scope 3 emissions reliability.

III.2.1 Direct Influence Matrix Construction

The MICMAC analysis began with the construction of a direct influence matrix (Table 3-5), where each of the 19 identified challenges was evaluated for its influence on and dependence upon the others. Binary values were assigned to represent these relationships, with 1 indicating a direct influence of one factor over another and 0 indicating no direct influence.

The construction of the matrix was based on three complementary sources:

(1) insights from the structured literature review,

(2) patterns and statements coded from the expert survey, and

(3) interpretive synthesis by the authors, using thematic co-occurrence and reported cause–effect relationships.

For example, one expert noted that manual data entry compromises accuracy and could be mitigated through automation and upgraded software. This informed a directional link from C11 (Automation, AI, and Real-Time Tracking) to C04 (Manual Data Entry and Human Error). Another respondent described how knowledge gaps and poor communication limit the ability of suppliers to share product-specific data, justifying a link from C02 (Supplier Readiness, Trust, and Cooperation) to C08 (Supplier Data Quality and Consistency). Similarly, another expert emphasized that training suppliers and aligning procurement with sustainability teams would improve communication, supporting a link from C03 (Expertise, Training, and Knowledge Gaps) to C01 (Communication and Data Sharing).

III.2.2 Matrix Elevation

To capture indirect effects, the influence matrix was raised to successive powers until stability was reached at power 3. This process, implemented via a Python script, revealed higher-order interactions and latent drivers. Influence and dependence coordinates (i, d) were then calculated for each variable, with results presented in Table 3-6.

III.2.3 Systematic Classification of Key Factors Influencing Scope 3 Emissions Reliability in Procurement

The MICMAC structural analysis enabled the classification of the 19 identified challenges into five systemic categories based on their calculated influence and dependence scores: drivers, linkages, dependents, autonomous, and peloton variables. This typology, derived from Table 3-6, is visually represented in the influence–dependence map (Figure 3-6). It provides a strategic foundation for interpreting the systemic role of each challenge and informing intervention priorities.

Table 3-5 Direct Influence Matrix of Scope 3 Reliability Factors

	Challenges	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	Influences
C01	**Communication and Data Sharing**	0	1	0	0	0	0	0	0	1	1	1	0	1	1	1	1	0	1	1	10
C02	**Supplier Readiness, Trust, and Cooperation**	1	0	0	0	1	0	0	1	1	1	1	0	1	1	0	0	0	0	1	9
C03	**Expertise, Training, Knowledge Gaps and Understanding**	1	1	0	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	15
C04	**Manual Data Entry and Matching, and Human Errors**	1	0	0	0	0	0	1	0	1	1	1	0	0	1	0	0	0	0	1	7
C05	**Inconsistent Supplier Methodologies**	0	1	0	0	0	0	0	1	1	1	0	0	1	1	0	0	0	0	1	7
C06	**Methodologies and Emissions Calculations**	0	0	0	0	0	0	1	0	1	1	1	1	0	1	0	1	1	1	1	10
C07	**Data Aggregation from the Use of the Spend-Based Approach**	0	0	0	1	1	1	0	1	1	0	0	0	1	1	0	1	0	1	1	10
C08	**Supplier Data Quality and Consistency**	0	0	0	1	1	1	1	0	1	1	0	0	1	1	1	1	0	1	1	12
C09	**Challenges in Data**	1	0	0	1	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	14
C10	**Procurement Platform Integration for Carbon Accounting**	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	1	1	1	9
C11	**Automation, AI, and Real-Time Data Tracking**	0	0	0	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	14
C12	**Software Capabilities for Emissions Data Processing**	0	0	0	1	0	1	1	0	1	1	1	0	0	0	1	0	1	0	0	8
C13	**Data Collection**	0	0	0	1	0	1	1	0	1	1	1	1	0	1	1	0	0	0	1	10
C14	**Data Verification**	0	0	0	0	0	0	0	0	1	1	0	0	1	0	1	1	0	1	1	7
C15	**Standardization and Regulatory Alignment**	1	1	0	0	1	1	1	1	1	1	0	0	1	1	0	1	0	1	1	13
C16	**Weak Governance and Unclear Policies**	1	1	1	0	0	1	0	0	1	1	0	0	1	1	1	0	0	1	1	11
C17	**Cost, Time, and Resource Constraints**	0	0	1	0	0	1	1	0	1	1	1	1	1	0	1	0	0	1	0	10
C18	**Aligning Procurement with Sustainability Goals**	1	1	1	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	1	7
C19	**Transparency**	1	1	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	1	0	9
Dependencies		8	7	3	7	4	10	10	6	17	16	10	5	15	15	12	12	6	13	16	192

Table 3-6 Dependency and Influence Score and Rankings of Key Factors

Code	Influence (i)	Dependence (d)	Influence Rank	Dependence Rank
C01	1037	898	3	19
C02	921	724	11	9
C03	1516	338	9	13
C04	730	650	15	10
C05	703	347	8	14
C06	1010	976	16	18
C07	944	911	17	16
C08	1144	582	1	15
C09	1376	1634	13	6
C10	960	1531	6	11
C11	1385	934	10	7
C12	868	568	7	1
C13	1011	1562	19	2
C14	735	1524	2	4
C15	1255	1311	12	17
C16	1139	1358	18	8
C17	1096	591	14	12
C18	747	1414	4	5
C19	929	1653	5	3

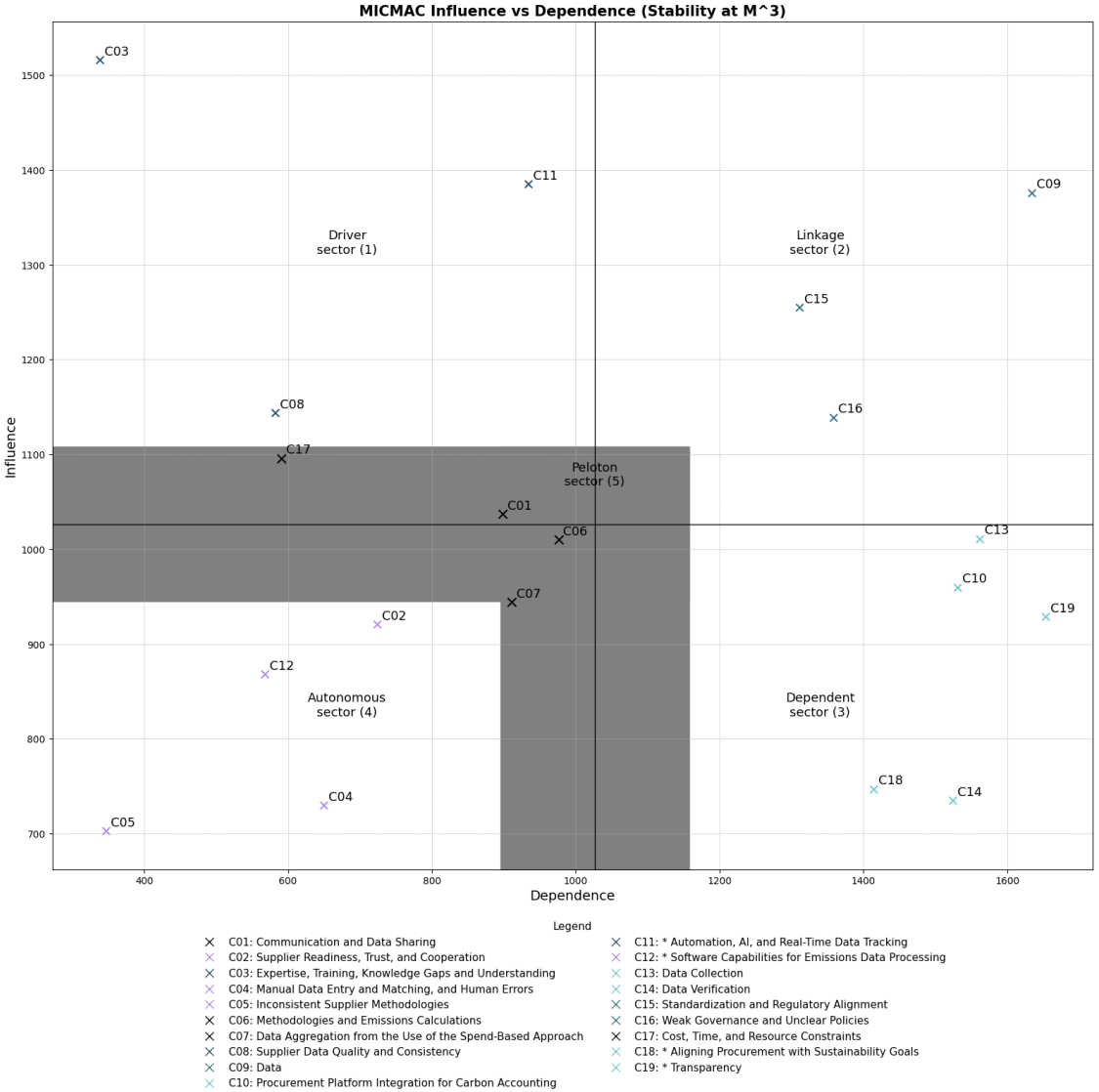


Figure 3-6 Influence-Dependence Map

Driver Variables : Bottom Axis (Leadership)

Driver variables show high influence and low dependence, making them powerful levers for systemic transformation. These include: C03 – Expertise, Training, Knowledge Gaps and Understanding; C08 – Supplier Data Quality and Consistency; C11 – Automation, AI, and Real-Time Data Tracking. They align with the Learning & Growth perspective of the SBSC, as they build foundational capacity and are linked with informational and human (intangible) capitals. Addressing C03 strengthens methodological competence and organizational know-how; enhancing C08 ensures robust, reliable data foundations; and advancing C11 supports digital integration for real-time, scalable emissions management. Together, these drivers initiate systemic improvement and continuous learning.

Linkage Variables : Intermediate Axis (Deployment)

Linkage variables combine high influence and high dependence, acting as key intermediaries within the system. These include: C09 – Challenges in Data; C15 – Standardization and Regulatory Alignment; C16 – Weak Governance and Unclear Policies. Positioned on the intermediate axis, they connect strategic intent to operational reality. However, their dual nature also introduces instability if not properly supported. Overcoming these requires cross-sector coordination (i.e., technical, regulatory, and institutional) to ensure systemic alignment and effective deployment of sustainability frameworks.

Dependent Variables : Top Axis (Outcomes)

Dependent variables are highly sensitive but low in influence, representing the Outcome perspective in the SBSC. These include: C10 – Procurement Platform Integration for Carbon Accounting; C13 – Data Collection; C14 – Data Verification; C18 – Aligning Procurement with Sustainability Goals; C19 – Supplier's Transparency. They capture downstream results and reflect the maturity of the overall system. For instance, C19 (Transparency) and C10 (Platform Integration) depend on the strength of corporate governance, data quality, and expertise. These variables should therefore be viewed as results and considered as indicators of success, evidence of effective upstream management, rather than independent levers for change.

Autonomous and Peloton Variables : Context-Based Factors

Autonomous variables (low influence and dependence) and Peloton variables (moderate influence and dependence) occupy more fluid positions. They can be linked to any SBSC perspective to enhance decision coverage and adapt strategies to specific contexts. Autonomous variables (C02, C04, C05, C12) represent localized or external challenges (e.g., supplier cooperation, manual errors, software limitations) with limited systemic propagation. Peloton variables (C01, C06, C07, C17) reflect transitional elements where importance shifts with context. For example, C01 (Communication)

fosters coordination, C06 (Methodologies) anchors consistency, C07 (Spend-Based Aggregation) supports practicality, and C17 (Cost and Resources) governs feasibility. Together, these variables enhance adaptive management, ensuring flexibility and broader decision coverage across the SBSC dimensions.

This classification offers a strategic lens for interpreting Scope 3 dynamics and prioritizing interventions addressed in the next section.

III.3 Roadmap-Based Recommendations for Scope 3 Emissions Accounting Using the SBSC Framework

Improving the reliability of Scope 3 emissions data in procurement requires a systemic transformation beyond technical solutions. Based on the MICMAC analysis, several high-influence challenges, particularly those related to expertise and training, supplier data quality, and digital integration, were identified as strategic entry points for change. To guide such transformation, a strategy map was developed and structured around the SBSC framework. Figure 3-7 translates the interdependencies uncovered through structural mapping into targeted recommendations across six interrelated perspectives. These dimensions reflect organizational capabilities, technical practices, governance structures, and financial systems necessary to advance credible Scope 3 emissions reporting. Appendix 3-4 summarizes how the MICMAC results are translated into actionable implementation details within the SBSC framework.

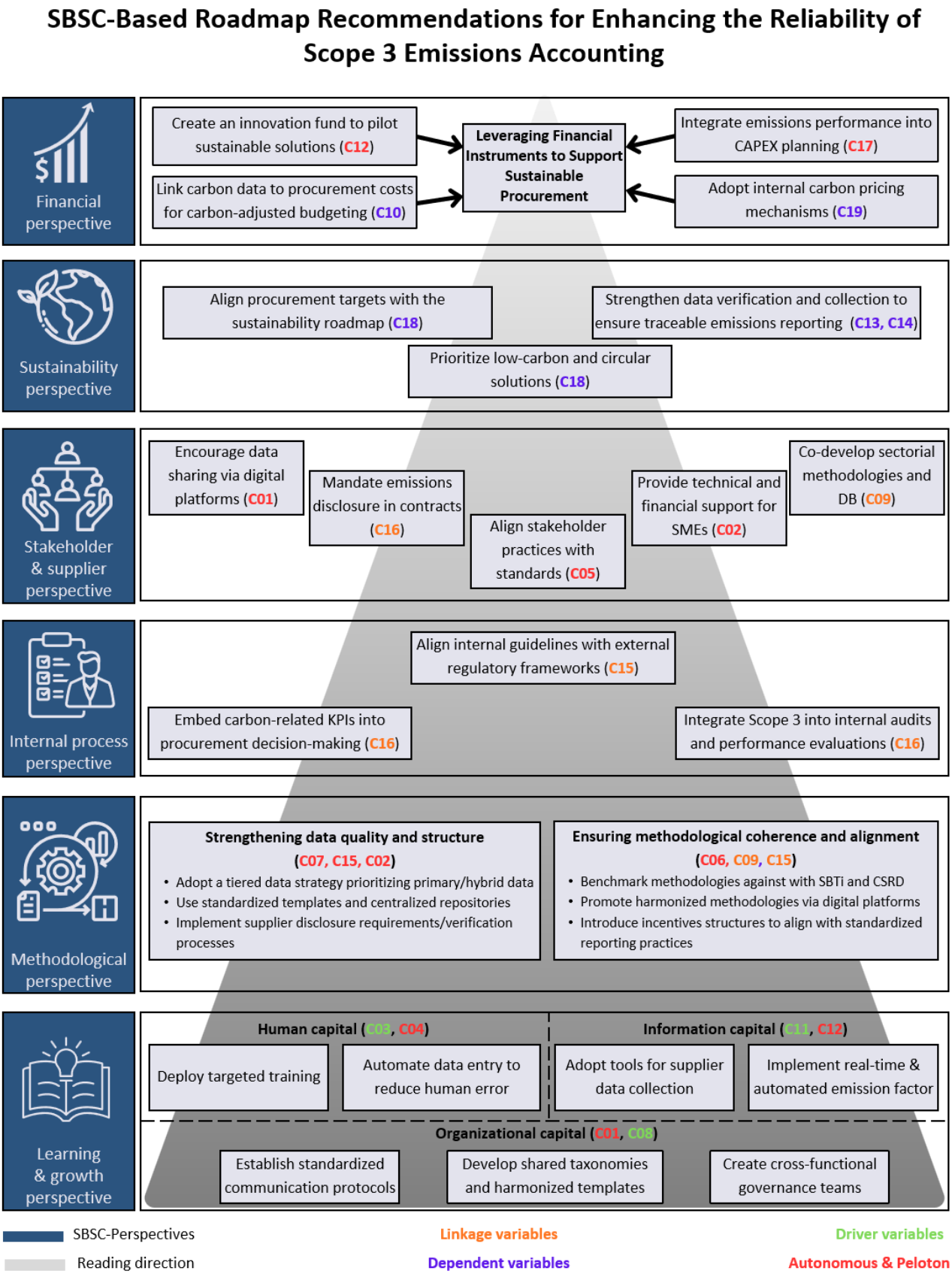


Figure 3-7 Strategic Roadmap for Enhancing Scope 3 Emissions Reliability in Procurement Using the SBSC Framework

IV. Discussion

The following discussion synthesizes the study's key findings, explores their methodological and managerial implications, and proposes practical pathways for enhancing the reliability of Scope 3 emissions accounting in procurement and beyond.

IV.1 Methodological Contributions and Practical Internal Application

The systemic structural analysis using MICMAC offers nuanced insights into the interdependencies affecting the reliability of Scope 3 emissions in procurement. By classifying variables as drivers, linkages, dependents, autonomous, and peloton, the study identifies strategic entry points for targeted interventions. The structured diagnosis is further supported by the 6M framework, which organizes challenges across key organizational domains in line with principles of continuous improvement. This systemic lens aligns with Life Cycle Management (LCM), emphasizing iterative enhancement of sustainability performance across the value chain and enabling broader applicability beyond procurement, including logistics, product use, and end-of-life phases.

Beyond methodological combination, the study advances a theoretical contribution by operationalizing how organizations build dynamic capabilities for Scope 3 data reliability through system-based learning. The integrated framework (6M–MICMAC–SBSC) conceptualizes the translation of dispersed technical challenges into structured managerial levers, linking operational data flows to strategic governance mechanisms. In doing so, it extends existing sustainability management literature—typically fragmented between technical, managerial, and reporting domains—by providing a unified architecture that explains how systemic reliability emerges from multi-level interactions rather than isolated improvements.

Building on this foundation, this study contributes a multi-level methodological approach that combines qualitative content analysis (NVivo), systemic structural mapping (MICMAC), categorical classification (6M), and strategy mapping (SBSC). Each component serves a distinct and sequential purpose: PRISMA ensures transparency and traceability in the literature base; NVivo extracts empirical and conceptual patterns; 6M structures these patterns into managerial categories; MICMAC quantifies interdependencies to reveal systemic leverage points; SBSC translates these insights into actionable strategy and management priorities.

This progression reflects a coherent methodological chain moving from evidence identification to system diagnosis and strategic alignment.

Compared to existing studies that typically address isolated dimensions, such as data infrastructure and digital tools (Baehr et al., 2024), or measurement frameworks and managerial practices (Vieira et al., 2024), this integrated framework captures the interaction between technical and strategic levers

essential for enhancing Scope 3 reliability. By linking data, systems, and strategy, it responds to the growing call in the literature for more holistic and operationalizable methodologies in sustainability research.

Beyond its research implications, the MICMAC framework offers a valuable practical tool for internal organizational application. Companies can utilize this method to identify and address their specific contextual challenges regarding Scope 3 emissions reliability. By collaboratively selecting key organizational factors, populating the influence-dependence matrix, stabilizing it using the computational method provided, and categorizing factors accordingly, companies can systematically generate tailored strategic roadmaps. Informed by MICMAC insights, the SBSC roadmap delivers precise, actionable objectives that align closely with organizational resources, priorities, and operational contexts.

Although the present study centers on procurement, the 6M–MICMAC–SBSC sequence is designed as a replicable pathway for category-specific applications that offers methodological transferability with adaptation. Extending it to other Scope 3 categories such as investments (Category 15) or downstream transportation and distribution (Category 9) involves re-specifying the variable universe to each category's data-generation mechanisms, boundaries, and actors. For example, this includes portfolio data-quality scoring for investments (Khatwani et al., 2024), and activity-based logistics indicators such as tonne-kilometres, load factors, and empty runs for transportation (Smart Freight Centre GLEC, 2024). The influence–dependence matrix is then rebuilt with domain experts and its stability rechecked; SBSC priorities are subsequently recalibrated. In this way, the method proceeds continuously across categories via re-elicitation and pilot iteration, while preserving the same stepwise logic.

IV.2 Strategic and Managerial Implications: Cross-Functional Integration, Capacity Building, and Technological Innovation

This study underscores several critical managerial insights for effectively enhancing Scope 3 emissions reliability. Procurement and sustainability managers are advised to strategically prioritize investments in key driver variables such as supplier data quality, staff training, internal communication, and digital automation systems, as these factors have substantial cascading impacts across organizational systems (Anilkumar E.N. & Sridharan R., 2019). For instance, improvements in supplier data quality and digitalization have been empirically linked to greater transparency and accuracy in emissions reporting (Wang et al., 2019).

Additionally, clearer regulatory guidelines and harmonized methodological standards are essential to achieving consistent and comparable Scope 3 emissions reporting (Downar et al., 2021). Regulatory-

corporate harmonization reduces ambiguity and fosters industry-wide best practices.

Cross-functional integration emerges prominently as another strategic necessity (Busse et al., 2016). Effective management of Scope 3 emissions demands robust collaboration among procurement, sustainability, finance, and IT departments. Organizations should establish integrated digital platforms, cross-departmental sustainability committees, shared accountability frameworks, and common performance metrics (Varaniūtė et al., 2022). Such integration is essential for coherent data governance and alignment with strategic goals, as highlighted in recent empirical studies (Shekarian et al., 2022)

Parallel to integration efforts, ongoing organizational training and capacity-building initiatives are crucial. Addressing internal expertise and methodological knowledge gaps identified within this study, structured education programs, certification initiatives, scenario-based training modules, and digital learning platforms should be institutionalized (Mena et al., 2013). Such sustained initiatives enhance organizational capabilities, directly improving emissions reporting quality and fostering deeper organizational commitment to sustainability objectives.

Technological innovation further represents a significant enabler for addressing systemic challenges, notably those related to automation, real-time tracking, and data transparency. Strategic investments in technologies such as blockchain, IoT, and AI-driven analytics can substantially enhance data quality, accuracy, and verification capabilities (Saberi et al., 2019). Viewing these technologies not merely as compliance measures but as long-term strategic assets gives competitive advantage, resilience, and sustainability leadership.

IV.3 Sectoral and Geographical Variability, and Long-term Strategic Implications

An essential consideration emerging from this analysis is the potential variation in identified challenges and proposed solutions across different sectors and geographical contexts. The systemic factors and recommendations presented may manifest differently depending on specific industrial contexts, such as manufacturing versus service sectors, or company size, particularly between large enterprises to SMEs (Álvarez Jaramillo et al., 2019; Trumpp et al., 2015). Regional regulatory environments and market structures also significantly influence Scope 3 emissions reporting challenges and solutions. This observation echoes contingency theory, which posit that organizational practices and structures must be adapted to contextual variables in order to be effective.

Finally, implementing robust Scope 3 emissions management practices has profound long-term strategic implications beyond compliance concerns. Effective Scope 3 accounting significantly enhances corporate reputation, regulatory alignment, investor attractiveness, and market differentiation, positioning organizations advantageously within the evolving sustainability landscape

(Eccles et al., 2014). Strategic investment in Scope 3 reliability should thus be viewed as both an operational imperative and a strategic opportunity, equipping organizations to proactively adapt to emerging regulatory frameworks, shifting market dynamics, and stakeholder expectations, thereby securing long-term organizational resilience and sustainability leadership (Gerged et al., 2021).

IV.4 Limitations and Future Research Directions

While the study offers a robust methodological contribution, several limitations should be acknowledged. The MICMAC analysis relies on expert judgment, which introduces subjectivity in evaluating inter-variable relationships. Although mitigated through literature triangulation and expert validation, interpretation bias may persist. The qualitative coding process using NVivo also involves researcher judgment, which may affect categorization outcomes. An alternative approach could involve a socio-economic lens, incorporating organizational dysfunctions that disrupt expected causal relationships (Savall & Zardet, 2008). Another opportunity, would be to introduce an interactive control systems (Simons, 1994), helping to detect new strategic and emerging uncertainties and enhancing adaptive learning during analysis.

Another limitation concerns expert selection and representativeness. The relatively small number of experts, while acceptable in qualitative management research, constrains the generalizability of findings. According to contingency theory, expert input may not fully capture the diversity of sectoral practices, supply-chain maturity levels, or regional contexts. Future studies should therefore involve a broader and more heterogeneous expert panel to strengthen external validity. Moreover, the restriction to English-language literature may have excluded relevant regional studies or grey literature, particularly from non-English-speaking contexts where Scope 3 reporting practices are evolving rapidly. Including multilingual sources could provide a more comprehensive and globally representative evidence base.

The current model also offers a static snapshot of interdependencies, without accounting for dynamic changes in relationships over time or under shifting regulatory and technological conditions. Periodic model updates and the integration of longitudinal or dynamic modeling approaches would therefore enhance temporal validity. Furthermore, the absence of real-world case studies limits the empirical validation of the proposed roadmap. Field-based pilots and organizational case applications are necessary to test the framework's practical relevance and operational feasibility.

Using complementary research methods could reinforce the robustness of the results by providing more thorough validation. Delphi rounds could be conducted to reduce subjectivity and promote structured consensus across a diverse panel of experts. Hybrid approaches integrating fuzzy MICMAC (Nida et al., 2024), Analytic Hierarchy Process (AHP) (Russo & Camanho, 2015), and Decision-Making

Trial and Evaluation Laboratory (DEMATEL) (Si et al., 2018) could further strengthen reliability by providing complementary quantitative assessments of influence and dependence. For example, fuzzy MICMAC can be operationalized by transforming binary influence matrices into fuzzy influence matrices using linguistic variables (e.g., low, medium, high), which are then converted into triangular fuzzy numbers to capture uncertainty. Subsequent AHP weighting can quantify expert confidence levels, while DEMATEL can validate causal directionality and feedback strength. Together, these steps provide a replicable pathway to enhance precision, transparency, and reproducibility in future applications of the MICMAC framework.

Subsequent pilot projects could rebuild the MICMAC matrix and recalibrate SBSC priorities for additional Scope 3 categories, to assess category-specific performance. Integrating these validation mechanisms within such pilots would help test not only the stability of the influence–dependence structure but also the practical transferability of the roadmap. Longitudinal studies would be especially valuable to observe how organizations adopt and internalize the roadmap over time, and how this affects data reliability, integration, and strategic decision-making. Tracking implementation outcomes before, during, and after roadmap adoption would provide critical insights into its practical impact.

Additionally, integrating MICMAC with dynamic modeling tools and investigating the role of emerging digital technologies (e.g., AI, blockchain, IoT) in enhancing Scope 3 data quality present promising directions for future inquiry.

V. Conclusion

This study provides a systemic and strategic investigation into the factors influencing the reliability of Scope 3 emissions accounting in procurement. By integrating qualitative content analysis (NVivo) with structural systems thinking (MICMAC), the research identifies and classifies key challenges into five systemic roles-driver, linkage, dependent, autonomous, and peloton variables, based on their influence and dependence within the emissions data ecosystem. The strategy map, structured through a Sustainability Balanced Scorecard (SBSC) framework, translates these findings into actionable guidance for organizations to enhance carbon accounting.

The study advances the understanding of Scope 3 emissions by revealing how technical, organizational, and governance factors interact to shape data reliability. It highlights that improving Scope 3 reporting requires addressing these interdependencies rather than isolated issues of data quality or methodology. This systemic perspective shows that expertise, supplier engagement, and digital integration function as mutually reinforcing levers that determine the effectiveness of corporate decarbonization strategies. These insights contribute to the literature by reframing Scope 3 reliability

as a dynamic outcome of interconnected managerial, procedural, and infrastructural variables.

Beyond these substantive insights, the study introduces an integrated 6M–MICMAC–SBSC framework that links diagnostic analysis with strategic implementation. This methodological sequence operationalizes complex relationships into a practical roadmap for decision-makers, allowing organizations to prioritize interventions based on systemic influence and dependence. The framework thus bridges the gap between analytical diagnosis and managerial execution, providing a replicable tool for addressing reliability challenges not only in procurement but across other Scope 3 categories.

Several managerial implications stem from this work. Cross-functional collaboration, training and capacity-building, and technological investment are identified as essential enablers for transitioning to more reliable and verifiable Scope 3 reporting. The study underlines the importance of harmonizing methodologies and regulatory frameworks to reduce variability and enhance comparability across sectors and regions.

In combining these insights, the study demonstrates that its novelty is both substantive and methodological, deepening understanding of the systemic drivers of Scope 3 reliability while providing a structured, operational framework for improvement. As regulatory pressures increase and corporate climate commitments deepen, the need for actionable and well-founded management tools to get reliable Scope 3 carbon data will only grow.

4| Hybrid Environmental Accounting for Procurement: Methodology and Industrial Applications

The previous chapters have established a comprehensive foundation for understanding the methodological and practical limitations of current Scope 3 emissions accounting, particularly in the context of procurement, within the framework of the GHG Protocol. Chapter 2 examined the theoretical foundations and accounting practices for assessing Scope 3 emissions in organizational procurement, including the integration of environmental and social data. It reviewed key frameworks, such as life cycle and environmentally extended input-output approaches, and highlighted procurement-level methodologies and challenges. Chapter 3 explored key implementation challenges. These include data inconsistency, limited data availability, heterogeneous supplier practices, low methodological standardization, and poor integration between procurement systems and carbon accounting tools. Collectively, these issues compromise the reliability, comparability, and strategic value of Scope 3 emissions disclosures.

In response, this chapter presents a structured methodology for hybrid and semi-automated emissions accounting in procurement, aimed at improving precision and scalability in Scope 3 assessments. It is organized into three parts:

***Section A** outlines the tiered hybrid framework combining monetary and physical data;*

***Section B** applies the model to real procurement datasets through a case study with Eiffage; and*

***Section C** discusses the methodological challenges and the need for standardized data, supplier engagement, and digital tools to enhance reporting accuracy and comparability.*

A. Toward a Hybrid and Automated Model for Procurement Emissions Accounting

This section proposes a hybrid and semi-automated calculation framework designed to improve data integration, reliability, and scalability in the calculation of procurement-related Scope 3 emissions based on data from accounting and procurement systems. Specifically, this approach is tailored to the French industrial and service sectors, where existing national and European datasets provide a rich but underused foundation for environmental modeling. Due to its detailed sectoral coverage and alignment with European classifications like NACE, EXIOBASE is the most suitable monetary database for representing the French economy at the macro-economic level (Stadler et al., 2018).

To ensure completeness and granularity, this hybrid model integrates both spend-based approach using monetary emission factors drawn from EEIO-based sources such as EXIOBASE and physical data extracted from process-based LCI databases or LCA studies. These secondary datasets are complemented, where available, by primary data from stakeholders such as supplier-specific emission factors, and product-level environmental declarations (e.g., PEF, EPDs).

This hybrid approach is thus defined as the integration of monetary and physical data sources, selected based on data availability and data quality at the product or sector level. It allows users to dynamically allocate either top-down or bottom-up data for each procurement line item, using an automated classification algorithm that prioritizes the most granular and robust data source available.

To clarify the terminology, top-down and bottom-up approaches are distinguished here by the structure, resolution, and origin of activity data. A bottom-up approach uses specific, disaggregated activity data, typically drawn from process-based inventories or supplier declarations. For instance, if a company has access to data showing that 1 kg of purchased aluminum emits 10.6 kg CO_2eq, and it procures 200 kg, this would constitute a bottom-up calculation. In contrast, a top-down approach applies when the organization has only aggregated or generalized data, often in the form of financial expenditures, such as total euros spent per category, which are then matched to average emission factors from EEIO databases. In some cases, even when procurement data begins as expenditure records, it can be transformed into a bottom-up analysis if the purchased products are homogeneous and their unit prices are known, allowing for accurate estimation of physical quantities. For example, if an organization purchases €10,000 worth of standardized office paper at €1 per ream, it is possible to deduce that 10,000 reams were procured. These quantities can then be directly linked to process-based LCI datasets, enabling product emission estimates despite the initial top-down inventory of the data (ISO 14072, 2024; UNEP, 2015).

Ultimately, the model allows flexible assignment of both monetary and physical data in top-down or bottom-up form, depending on what is available for each procurement line. From a methodological standpoint, this approach is best classified as a Systematic Tiered Hybrid Life Cycle Assessment (STHL). This classification is supported by several methodological features that distinguish the model from conventional hybrid LCA methods (Agez et al., 2020b; Nakamura, 2023; Suh, 2009):

- First, the integration of data is not ad hoc, but follows a rule-based logic that dynamically selects the most appropriate data source for each procurement category or supplier, depending on data availability, resolution, and confidence level.
- Second, the model is partially automated, allowing for efficient, reproducible, and scalable analysis, unlike traditional Tiered Hybrid LCA which rely on manually defined system boundaries.
- Third, it minimizes truncation and aggregation errors by filling process-data gaps with EEIO coefficients only where necessary, while ensuring methodological consistency and traceability.
- Finally, the workflow is carefully designed to avoid double counting, a common issue in hybrid models. This is achieved by clearly defining the boundaries between different data sources and applying rules to exclude any information that would be counted twice.

Thus, unlike other hybrid approaches such as Matrix Augmentation (which alters the IO matrix structure) or Path Exchange (which selectively replaces EEIO paths with process data), this model retains the core EEIO structure while layering process-specific detail through a structured overlay. It also stops short of the Integrated Hybrid LCA (IHL) method, which requires a mathematically intensive full-system integration that would be computationally prohibitive and overly complex for procurement-focused applications (Crawford et al., 2018; Hagenaars et al., 2025).

This structure minimizes truncation errors, by systematically filling data gaps with EEIO emission factors only when specific process-based data is unavailable, while preserving completeness, and it aligns well with the methodological demands of Scope 3 Category 1 emissions under the GHG Protocol (WRI and WBCSD, 2011a). It also ensures flexibility, enabling organizations to adapt the model based on sector-specific constraints, data maturity, and supplier engagement levels, as previously identified in Chapter 3.

The following sections present the methodological development of the proposed hybrid environmental accounting framework. This includes the construction of successive modeling tiers, from a top-down monetary approaches based on standardized classification systems in France and Europe, to a more granular bottom-up model incorporating physical data and supplier-specific information where available. These tiers are then integrated into a hybrid decision tree, enabling the automated and dynamic allocation of environmental intensities to procurement records based on data

availability, resolution, and specificity. This structured and rule-based automation is essential for ensuring scalability, consistency, and reproducibility, particularly in large and heterogeneous procurement datasets.

I. Sector-Level Environmental Accounting Using a Top-Down Monetary Model

This section contributes to an article by Essouid et al., "Integrating Social and Environmental Intensities into Procurement-Based LCSA: A Sector-Level Framework for France", which is currently under finalization.

I.1 Introduction

To operationalize the hybrid framework described previously, we first implement a top-down monetary model. This approach serves as a scalable starting point when procurement records are primarily monetary and product-level physical data is unavailable (Huang et al., 2009a). For instance, if a company knows it spent €25,000 with Supplier Y over a given period but lacks information on the specific products or services procured, a top-down approach enables estimation of environmental impacts by assigning average sectoral intensities to the expenditure based on the supplier's economic activity classification. The top-down method enables broad coverage of Scope 3 emissions and other environmental impacts mapping expenditure categories to sectoral environmental intensities derived from EXIOBASE v3.8.1 (2022 industry-by-industry "ixi" format), rather than the product-by-product ("pxp") format, as discussed in Chapter 2. The use of the ixi format reflects a sector-level approach, which aligns with the structure of available expenditure data (Stadler et al., 2018).

In this study, we apply the model to assess carbon footprint and water scarcity, testing the generalizability of the method across different environmental indicators. Environmental characterization in this study is performed using the Impact World 2002+ model, which provides midpoint indicators such as climate change and water scarcity, a measure of the pressure on local water resources relative to their availability (Agez et al., 2024; Bulle et al., 2019).

This model was selected for its compatibility with EXIOBASE, its open-source transparency, and its ability to efficiently process large-scale environmental accounting. Impact World+ offers a practical balance between comprehensiveness and computational performance, making it particularly well-suited for integrating with automated workflows (Bulle et al., 2019). These features make it a robust choice for assigning environmental intensities to procurement data across multiple indicators in this study.

I.2 Materials and Methods

This section presents the methodological framework used to estimate procurement-related environmental impacts using a top-down monetary model at the sector-level, detailing the classification systems, data integration steps, and computational tools employed.

I.2.1 Structure of Economic Sectors in France and Europe: Codification and Environmental Integration

The implementation of a top-down monetary model for environmental impact assessment in procurement contexts necessitates a precise mapping between economic activity classifications and the sectoral structure of EEIO databases. This mapping is particularly crucial when financial expenditure data, often aggregated by supplier or internal accounting category, is to be translated into environmental impacts using sector-specific emission intensities (Paepe et al., 2023). In the European and French contexts, this translation is facilitated by a set of harmonized classification and codification systems: NACE, NAF, APE, SIREN, and SIRET codes.

As explained in Chapter 2, NACE provides a four-level hierarchical structure that classifies economic activities from broad sectors to highly specific ones. These codes are not only used in economic statistics but also form the structural foundation of MRIO databases such as EXIOBASE, which disaggregate environmental intensities at the sector level across all EU member states.

In France, NACE codes are adapted under the Nomenclature d'Activités Française (NAF Rev. 2). While NAF codes maintain compatibility with NACE at the four-digit level, they also introduce additional national specifications at the five-digit level to allow more precise classification of economic activities within the French context (French Directorate for Legal and Administrative Information, 2025). Each legal entity operating in France is assigned a unique SIREN code (Système d'Identification du Répertoire des ENtreprises), which identifies the company as a whole, while each individual establishment or operating unit within the company is assigned a SIRET code (Système d'Identification du Répertoire des ETablissements) (French Directorate for Legal and Administrative Information, 2024). Crucially, each SIREN or SIRET is associated with a single APE code, which corresponds to the firm's primary economic activity as defined by the NAF classification. The APE (Activité Principale Exercée) is therefore not just a statistical label but a key operational attribute that enables systematic alignment between firm-level procurement data and environmental assessment models. In the context of this study, the NAF code serves as the linking node between administrative datasets (e.g., legal registries, procurement records) and EEIO models such as EXIOBASE.

These codification systems are central to our modeling approach because they act as bridges between financial records and environmental intensity databases. For instance, a supplier may be identified by

its SIRET, classified under a specific NAF code (e.g., 01.12Z – "Culture du riz"), which maps to a corresponding NACE category, and in turn to an EXIOBASE sector (e.g., 0112 – "Cultivation of rice"). This structured relationship enables systematic linkage of procurement spending to relevant environmental coefficients.

I.2.2 Calculation of Environmental Intensities Using EXIOBASE and pymrio

❖ *Conceptual Foundation: Consumption-Based Environmental Accounting*

This study adopts a consumption-based accounting (CBA) framework to calculate procurement-related environmental intensities. CBA here refers more broadly to an accounting perspective that attributes environmental burdens to the final consumer of goods and services, in this case, the procuring organization. Unlike production-based models, which assign emissions to the point of generation, this approach shifts the perspective upstream, capturing indirect impacts embedded in supply chains (Ozawa-Meida et al., 2013). This is particularly relevant for Scope 3 emissions, which arise from activities outside the organization's direct control.

The rationale for selecting a consumption-based approach is threefold:

- Attributional Accuracy: CBA ensures a more equitable and precise distribution of environmental responsibility. This is especially important for service-oriented or procurement-heavy organizations that may have limited operational emissions but substantial embedded environmental impacts through outsourced production.
- Alignment with International Standards: The methodology is consistent with leading environmental reporting frameworks, including the GHG Protocol Scope 3 Standard, ISO 14067, and the European Union's sustainable finance taxonomies. These frameworks emphasize the importance of capturing indirect, supply chain–related emissions to ensure a holistic view of environmental performance.
- Strategic Utility: CBA provides actionable insights into the full environmental cost of organizational expenditures, thereby supporting evidence-based interventions such as supplier engagement, sustainable procurement strategies, and climate-related financial disclosures.

❖ *Methodological Implementation: EXIOBASE and pymrio*

To operationalize this framework, the study employs EXIOBASE ixi in conjunction with the Python-based pymrio library (Stadler, 2021). EXIOBASE offers a multi-regional input-output (MRIO) representation of the global economy, including consistent datasets on monetary flows, environmental extensions, and final demand vectors for 49 countries and 163 economic sectors. Crucially, it includes disaggregated data for France, making it particularly well-suited for national-level

environmental accounting.

The pymrio library serves as a computational backbone for model implementation. It enables direct access to EXIOBASE matrices, including inter-industry transactions (M€), environmental satellite accounts, and Leontief inverses, and provides built-in functionality for applying customized characterization factors. This configuration facilitates a robust, scalable, and reproducible modeling framework.

Pymrio was chosen over other tools, such as PyIO and the MRIOlab suite , for its native compatibility with EXIOBASE, modular design, and open-source transparency, which are critical for automation, reproducibility, and customization in policy-relevant environmental accounting workflows. Its active maintenance and integration with standard scientific Python libraries also make it more suitable for embedding within larger analytical pipelines.

❖ *Computational Workflow*

The environmental intensity modeling follows a four-step computational sequence implemented via pymrio (Stadler, 2021), as detailed below:

- Data importation: The EXIOBASE database is loaded using pymrio.load_all(), which parses and structures the following matrices: Inter-industry transactions (Z), Final demand matrix (Y), Leontief inverse (L), Environmental satellite accounts (S)
- Characterization of satellite accounts: To convert raw emissions into midpoint impact categories, the model integrates characterization factors (CF) from the Impact World+ v2.0.1 method. These factors are mapped to EXIOBASE environmental flows and applied to the satellite matrix S (Equation 4-1), enabling quantification of impact categories such as climate change and water scarcity.

$$\boldsymbol{S_{impact} = CF \,.\, S}$$

Equation 4-1 Application of Characterization Factors

- Calculation of environmental impacts: The environmental propagation across the supply chain is modeled using the Leontief demand-driven approach. The characterized environmental burdens are multiplied by the Leontief inverse L, yielding a vector of indirect and direct environmental impacts associated with final demand (Equation 4-2).

$$\boldsymbol{Per - MEuro\ intensities = \frac{CF \,.\, D_{CBA}}{Y_{index}}}$$

Equation 4-2 Calculation of Environmental Intensities

Where: D_{CBA}=S.L.Y ; and Y_{index} is a pandas Series that contains: the total final demand values for each combination of region (country) and sector.

- Normalization by final demand: To calculate sector-specific environmental intensities (e.g., kg CO_2eq/€), the total environmental impacts are normalized by sectoral final demand, converting the initial M€ units to € using a factor of 10^6.

This workflow ensures transparency and scalability across multiple sectors and environmental indicators.

❖ *Inflation Adjustment and Monetary Harmonization*

A critical methodological consideration in monetary-based environmental modeling is the temporal harmonization of financial data with environmental intensity coefficients. EXIOBASE reports its economic and environmental data in constant 2022 euros. As a result, any financial expenditure data from subsequent years must be deflated to real terms to maintain methodological consistency.

To address this, an inflation adjustment module was implemented using official Consumer Price Index (CPI) values published by INSEE, the French national statistics agency. The applied inflation rates were: 2023: +4.9%, 2024: +2.0% (INSEE, 2025).

These rates yield a cumulative inflation factor of 1.070 for aligning 2022-based intensity coefficients with 2024 procurement data. Thus, all environmental intensities expressed per euro (e.g., kg CO_2eq/€ or m^3 eq/€) were scaled upward by this factor to ensure comparability with current expenditure data.

This inflation correction serves several methodological purposes (© Carbon+Alt+Delete, 2025):

- Mitigation of systematic bias: Using unadjusted intensities with nominal expenditures would result in an underestimation of environmental impacts, especially in an inflationary economic context.
- Temporal comparability: For multi-year trend analyses or scenario modeling, inflation normalization ensures that changes in environmental performance reflect structural shifts rather than price distortions.
- Methodological compliance: While the GHG Protocol does not explicitly require environmental intensities and financial data to be expressed in constant currency units, using constant currency is considered a best practice to ensure consistency, comparability, to preserve the validity of reported results over time.

Failure to apply appropriate inflation corrections can lead to significant misestimations, particularly in procurement categories experiencing high price volatility or rapid economic growth.

I.2.3 Semantic Mapping of NAF Codes to EXIOBASE Sectors

To assign environmental intensities to procurement records within the top-down model, it is necessary to map French economic activity codes (NAF) to EXIOBASE sectors. Since NAF codes are specific to the French statistical system and EXIOBASE categories are structured in English, a multi-stage workflow was developed to enable robust cross-lingual sectoral alignment. This process includes automated machine translation, semantic similarity modeling, manual validation, and final merging.

❖ *Translation of NAF Descriptions*

The process begins with the translation of NAF activity descriptions from French to English using the MarianMT model (Helsinki-NLP/opus-mt-fr-en). This neural machine translation model, based on the Marian framework, ensures linguistic consistency with EXIOBASE sector names and enables semantic comparison across classification systems (Lohar et al., 2023).

❖ *Semantic Embedding and Sector Matching*

Following translation, a semantic similarity algorithm is applied to match translated NAF descriptions to their closest EXIOBASE sector equivalents. Both EXIOBASE sector names and translated NAF descriptions are embedded in a shared high-dimensional vector space using transformer-based sentence embedding models from the sentence-transformers library. These models are designed to capture contextual similarity between short texts, enabling nuanced alignment even when surface wording diverges (Cho and Ackom, 2025).

To identify the most appropriate model for this task, we benchmarked three widely used sentence embedding models against a representative subset of translated NAF descriptions and EXIOBASE sector names:

- all-MiniLM-L6-v2: A lightweight, multilingual model optimized for computational speed and efficiency.
- all-mpnet-base-v2: A more accurate English-only model suited for technical and descriptive texts.
- BAAI/bge-large-en-v1.5: A state-of-the-art English embedding model optimized for semantic search and dense retrieval tasks.

These models were evaluated on semantic alignment accuracy, language support, and computational feasibility for large-scale deployment. The results are summarized in Table 4-1.

Table 4-1 Comparative Evaluation of Embedding Models for Product–LCI Matching

Model	**all-MiniLM-L6-v2**	**all-mpnet-base-v2**	**BAAI/bge-large-en-v1.5**
Language Support	Multilingual	English	English
Semantic Accuracy	2/5	3/5	4/5
Computation Cost	4/5	4/5	2/5
Strengths	Fast, low-resource	Richer representation for English input	Highest semantic fidelity for environmental use
Limitations	Low performance on technical categories	No multilingual capability	High computational cost, limited to English-only datasets

Among the models tested, BAAI/bge-large-en-v1.5 provided the best results for domain-specific similarity, consistently returning accurate EXIOBASE matches across diverse product categories. Given the need for semantic precision in sectoral alignment, this model was selected for production use in the mapping pipeline (Devlin et al., 2019).

Cosine similarity is used to quantify the closeness between embedded vectors, and each NAF code is linked to one or more EXIOBASE sectors based on the similarity score. Where applicable, mappings are ranked by confidence, and thresholding techniques are applied to filter low-relevance matches.

This embedding-based approach offers several advantages over traditional lexical matching techniques (e.g., fuzzy string matching):

- Semantic Robustness: The model captures contextual relationships, enabling more accurate matching across domains.
- Scalability: It supports batch processing across thousands of codes, facilitating automation.
- Noise Tolerance: Embedding models are more resilient to inconsistencies and ambiguities in short textual descriptions.

❖ *Manual Validation and Quality Assurance*

Following the initial embedding of NAF descriptions and EXIOBASE sector labels into a shared semantic space, cosine similarity scores are computed to rank candidate matches. These similarity scores form the quantitative basis for assigning sector classifications. To improve the reliability of the automated mapping, a manual validation step is performed. This includes a systematic review of:

- Matches with low similarity scores,
- NAF codes associated with multiple sectors showing minimal differences in ranking,
- Environmentally sensitive or ambiguous categories where inaccurate classification could distort impact estimates.

Where necessary, initial matches are adjusted or confirmed using official INSEE NAF descriptions and supplementary documentation. This ensures that each classification is semantically appropriate and consistent with the intended scope of economic activity.

Finalized mappings are consolidated into a master alignment table, which serves as the reference framework for assigning environmental intensities from EXIOBASE to procurement records. This combined approach, automating similarity scoring while retaining a layer of manual control, achieves a robust balance between scalability and interpretability, supporting the transparent and reproducible implementation of top-down Scope 3 environmental accounting.

❖ *Merging and Output Generation*

In the final step, validated NAF–EXIOBASE mappings are merged with the EXIOBASE environmental intensity dataset (impact / EUR2024). This enables each NAF code to be associated with a standardized environmental profile, which is then used in the impact allocation phase. The output is a harmonized mapping of environmental intensities per NAF, ready for integration with procurement records tagged by SIREN/SIRET codes.

This structured, linguistically robust process ensures that French legal and statistical identifiers can be reliably connected to international environmental accounting systems, enabling transparent and scalable Scope 3 emissions modeling.

I.2.4 Procurement Data Integration and Environmental Impact Calculation

This final stage of the modeling framework involves the integration of procurement datasets with environmental intensity profiles to produce supplier-specific and category-level impact reports. The objective is to translate financial transactions into meaningful environmental metrics using sectoral mappings developed in the preceding steps. This process encompasses four main components: data extraction, supplier classification, impact calculation, and output reporting.

❖ *Extraction and Preprocessing of Procurement Data*

Procurement data is extracted from enterprise resource planning (ERP) systems or accounting platforms such as SAP, Oracle, or Microsoft Dynamics. These systems typically provide detailed transactional records, including:

- Unique supplier identifiers (e.g., SIREN codes),
- Transaction dates and monetary amounts,
- Purchasing categories or internal cost centers,
- Descriptive fields such as invoice numbers, product descriptions, or item codes.

The resulting structured dataset represents the final demand vector in the top-down EEIO model. It forms the quantitative basis for allocating environmental intensities to individual procurement line items.

❖ *Identification of NAF Codes from SIREN Identifiers*

Each procurement record is linked to a supplier through a SIREN code, a unique identifier assigned to legal entities operating in France. To classify each supplier by its economic activity, the corresponding NAF code must be retrieved.

This classification step uses one of two sources:

- The SIRENE database maintained by INSEE, which provides official NAF codes for all registered businesses,
- Or internally maintained metadata provided by the procuring organization, where available.

This linking procedure is critical, as it enables the assignment of sector-specific environmental intensities to each procurement record by aligning suppliers with their appropriate EXIOBASE sector through the intermediate NAF code.

❖ *Impact Calculation at the Transaction Level*

Once each transaction is tagged with a NAF code, environmental intensities (impact/ EUR2024) derived from EXIOBASE are applied. These intensities are matched to each NAF sector based on the semantic mapping developed. The total environmental impact of each transaction is calculated by multiplying the expenditure amount by the corresponding intensity factor.

This procedure enables the allocation of environmental impacts across multiple dimensions, using structured procurement data and mapped sectoral information. The resulting dataset includes the following key columns:

- Supplier name and identifier (SIREN) – identify the legal entity responsible for the transaction.
- Economic activity classification (NAF code) – derived from the supplier's APE code via official registries.
- Mapped EXIOBASE sector – obtained through semantic matching with NAF activity labels.
- Expenditure (expressed in EUR2024) – used as the basis for calculating impacts.
- Carbone footprint (kg CO_2 eq) – result of applying carbon intensity coefficients to expenditures.

- Water scarcity impact (m^3 world eq) – result of applying water intensity coefficients to expenditures.

The result is a transaction-level inventory of Scope 3 environmental impacts across the procurement portfolio.

❖ *Output Generation and Reporting*

The final outputs of the model consist of a set of structured impact reports and data exports, generated in formats suitable for internal and external use. These include:

- Transaction-level footprints per procurement line item,
- Supplier-specific profiles, summarizing environmental impacts by SIREN code,
- Aggregated reports by purchasing category or NAF sector,
- Machine-readable exports in CSV or XLSX format for further analysis or system integration,
- Dashboard-ready datasets for visualization or business intelligence tools.

These results can be directly integrated into corporate reporting frameworks such as the CDP, CSRD, or used to update internal Scope 3 emissions inventories under the GHG Protocol. Beyond compliance, the model also supports strategic decision-making, such as supplier evaluation, procurement prioritization, and low-carbon sourcing initiatives. The methodology is designed to be scalable, transparent, and adaptable to a wide range of institutional contexts and environmental indicators. While the current implementation focuses on climate change and water scarcity, the framework is compatible with other midpoint indicators (e.g., land use, eutrophication) depending on the characterization model applied in the earlier steps (e.g., Impact World+).

I.2.5 Model Architecture

The overall architecture of the modeling framework is summarized in Figure 4-1, which illustrates the sequential flow of data from environmental intensity modeling to semantic sector mapping and procurement-based impact allocation. The figure outlines the main components and data transformations involved in generating transaction-level environmental footprints from procurement records.

I.3 Demonstration Results

To illustrate the model's real-world applicability, a demonstration was conducted using a curated procurement dataset composed of 100 anonymized financial transactions. This demo file served as the input for applying the full modeling pipeline, including supplier classification, sector mapping via NAF-to-EXIOBASE alignment, and the assignment of inflation-adjusted environmental intensities.

Table 4-2 presents a representative subset of this dataset, showing ten transactions across diverse economic activities, ranging from medical equipment manufacturing to electricity generation and food services. Each entry includes product type, product category and sector. This demonstration dataset forms the foundation for the analyses presented in Sections II and III, where multiple modeling approaches are tested, and the semantic alignment process is further evaluated. Building on this input, the top-down environmental intensity model is then applied to allocate carbon and water impacts across the dataset. Table 4-3 displays the resulting sector-level environmental resolution from this model. While only ten suppliers are shown for illustration, the model processes all transactions automatically, estimating each supplier's classification.

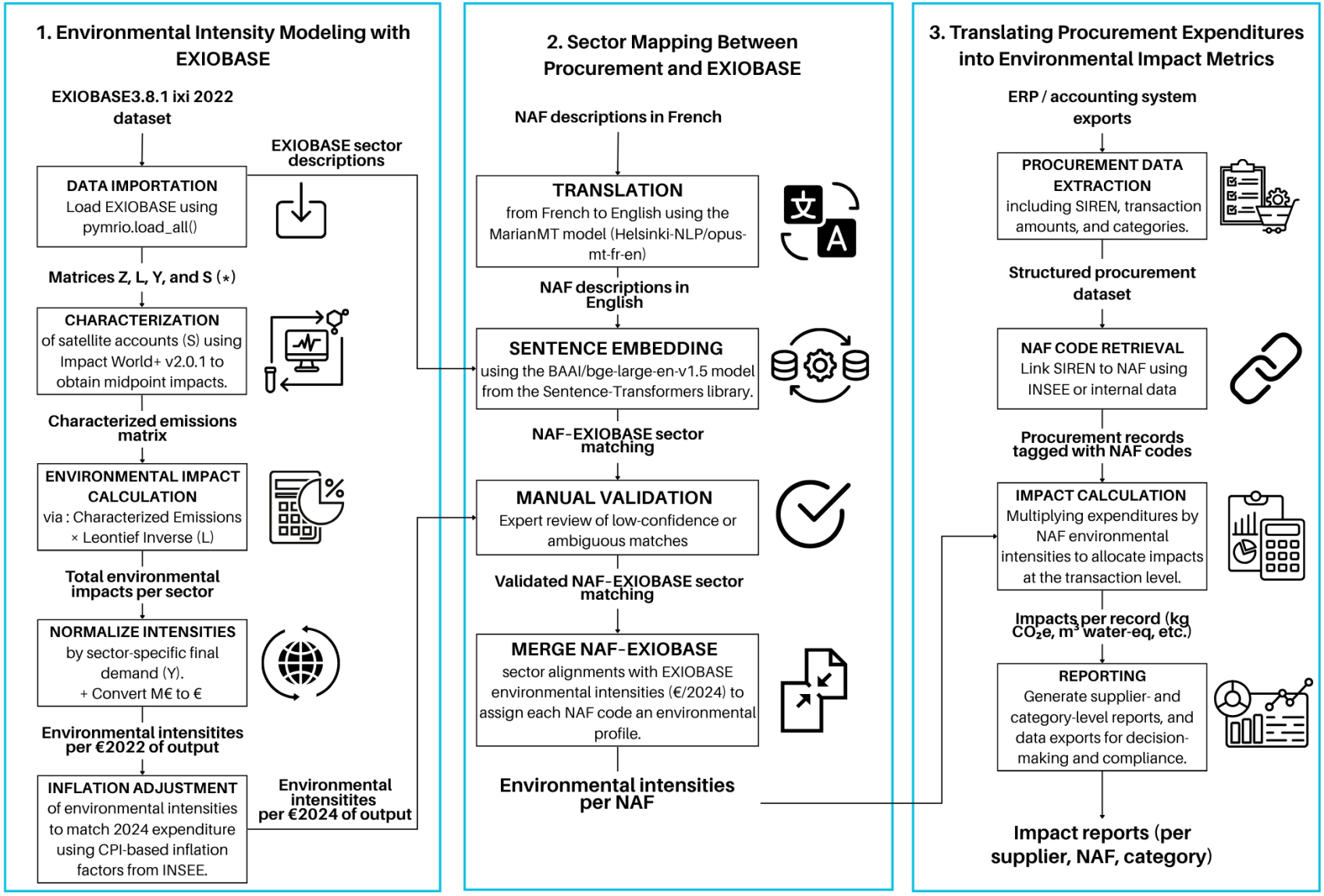


Figure 4-1 Methodological Workflow for Translating Procurement Data into Sector-Level Environmental Impact Metrics

Table 4-2 Representative Procurement Records Used for Model Demonstration

	Product	**Product Category**	**Sector**
1	PTFE-Nitinol Guidewire with a hydrophilic tip	Medical equipment	Manufacture of medical, surgical and dental equipment
2	Toner module for laser printer, black/white	Office machinery and accessories	Wholesale trade (business-to-business trade) of miscellaneous supplies and equipment for trade and services
3	Water works construction	Works relating to fluid networks	Other specialized construction work
4	Pizza with lardoons onions and cheese	Catering	Traditional restoration
5	Acrylic binding service	Binding and related services	Activities of head offices
6	Leather shoes imported from China	Footwear	Wholesale trade (business-to-business) of clothing and footwear
7	Excavation by skid-steer loader	Other specialized construction work n.e.c.	Sealing work
8	Raw chicken breast	Poultry meat	Retail trade services of meat and meat products in specialised stores
9	Medium voltage electricity	Electricity	Electricity generation
10	Softwood for carpentry	Other carpentry and framework elements (Wood)	Wood and PVC carpentry works

Table 4-3 Demonstration Output: Supplier-Level Environmental Impact Allocation Using Sector-Based Intensities

Supplier	SIREN	NAF	Sector	Exiobase sector	kg CO2 eq per EUR2024	m3 water eq per EUR2024	Expenditures (EUR2024)	kg CO2 eq	m3 water eq
S1	403683667	32.50A	Manufacture of medical, surgical and dental equipment	Manufacture of medical, precision and optical instruments, watches and clocks (33)	0.2017	0.1351	2000	403.451	270.133
S2	404942344	46.69C	Wholesale trade (business-to-business trade) of miscellaneous supplies and equipment for trade and services	Wholesale trade and commission trade, except of motor vehicles and motorcycles (51)	0.0612	0.0592	3500	214.124	207.042
S3	519764823	43.99D	Other specialized construction work	Construction (45)	0.2090	0.0893	12000	2507.905	1071.003
S4	539779272	56.10A	Traditional restoration	Hotels and restaurants (55)	0.0762	0.1293	1000	76.243	129.320
S5	853838043	70.10Z	Activities of head offices	Other business activities (74)	0.0706	0.0492	500	35.304	24.617
S6	791399603	46.42Z	Wholesale trade (business-to-business) of clothing and footwear	Wholesale trade and commission trade, except of motor vehicles and motorcycles (51)	0.0612	0.0592	4850	296.715	286.902
S7	950323675	43.99A	Sealing work	Construction (45)	0.2090	0.0893	8000	1671.937	714.002
S8	443858865	47.22Z	Retail trade services of meat and meat products in specialised stores	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods (52)	0.0353	0.0244	3980	140.640	97.002
S9	752234591	35.11Z	Electricity generation	Production of electricity nec	0.4802	0.3034	750	360.135	227.538
S10	478250418	43.32A	Wood and PVC carpentry works	Manufacture of wood and of products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials (20)	0.3594	0.2086	6900	2479.876	1439.078
Total							**43480**	**8186.329**	**4466.636**

These results are further visualized in Figure 4-2 to support supplier prioritization, risk assessment, and strategic procurement planning.

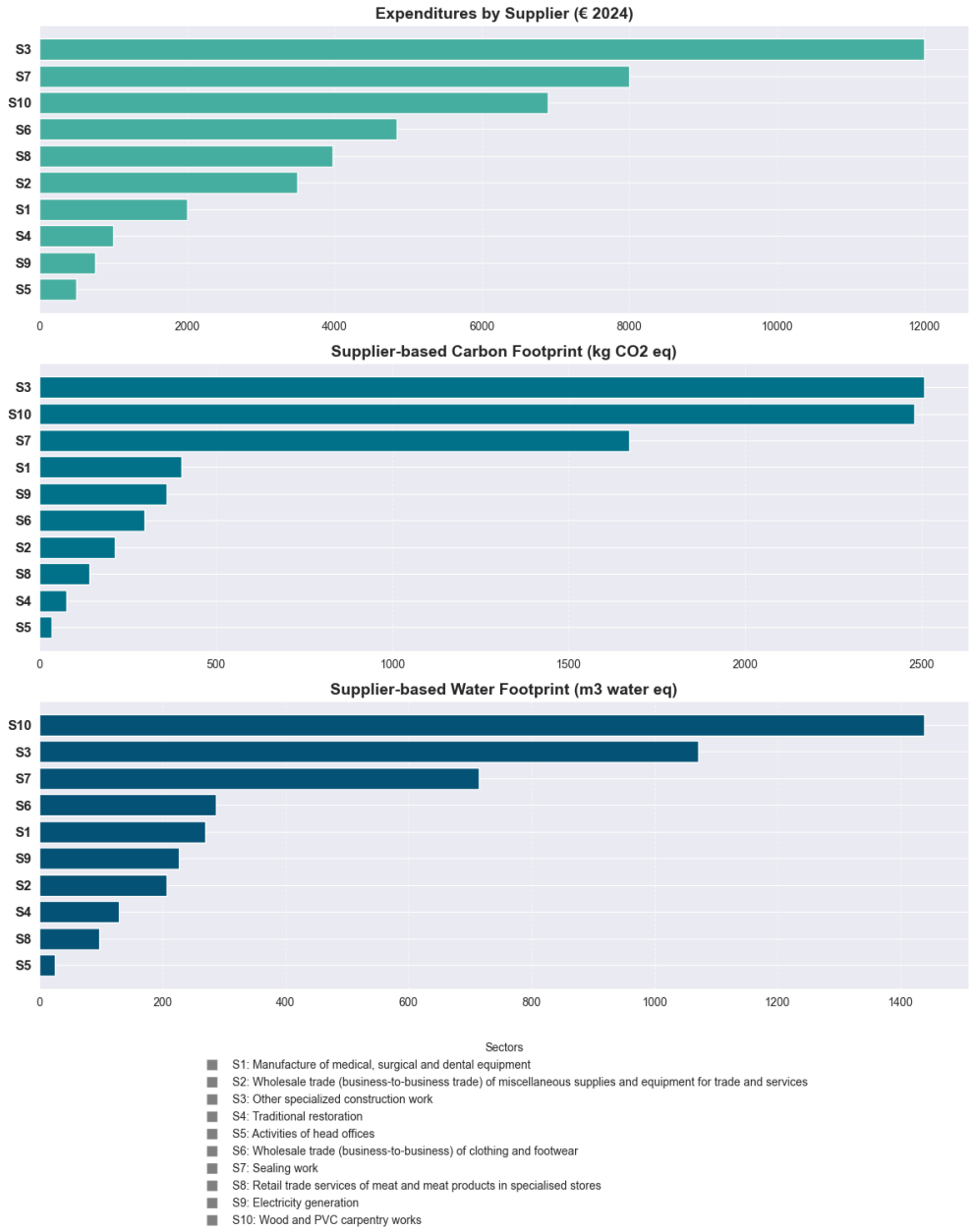


Figure 4-2 Bar Chart of Supplier-Level Environmental Impacts Using Sector-Based Intensities

The bar charts present the absolute values of expenditures, carbon emissions (kg CO_2 eq), and water scarcity (m^3 water eq) associated with each supplier. While these visualizations provide an initial overview of the distribution of financial and environmental impacts, the indicators are expressed in different units and thus are not directly comparable across charts. In this top-down modeling approach, environmental impacts are calculated by multiplying procurement expenditures by sector-specific environmental intensity factors. As expected, suppliers with higher spending often correspond to higher impacts; however, deviations from this pattern are analytically significant. For instance, some

suppliers, such as Supplier S1, exhibit relatively low expenditures but disproportionately high environmental impacts, indicating procurement from sectors with elevated carbon or water intensity. These cases highlight the model's ability to reveal not only high-volume transactions but also high-impact suppliers that might otherwise be overlooked. The comparability of suppliers in environmental terms, including normalization and relative rankings, will be further developed in the case study section.

I.4 Discussion

While the top-down modeling framework offers notable advantages, such as scalability, transparency, and alignment with standard accounting systems, it also presents several structural and methodological limitations that constrain its precision and applicability.

A primary challenge lies in the mismatch between the granularity of national activity codes (NAF) and the sectoral resolution of EXIOBASE. Even with the application of semantic embeddings to enhance concordance, EXIOBASE's 163-sector structure remains far coarser than the 732 five-character NAF subclasses (four digits plus one letter). This disparity creates aggregation issues, particularly in diverse or rapidly evolving sectors such as IT services, logistics, and creative industries. Compounding this, firms are typically assigned a single APE/NAF code regardless of the multiplicity of their operations, further distorting the representation of their actual environmental footprint (Bush et al., 2014; Stadler et al., 2018).

Second, the model assumes uniform environmental intensities across all firms within each mapped EXIOBASE sector. This sectoral homogeneity oversimplifies reality, as it ignores firm-level differences in production technologies, energy sourcing, and supply chain configurations. As a result, environmental impacts are often misestimated, especially in sectors characterized by wide internal variability (Lastauskas et al., 2024; Lenzen, 2000).

Third, the framework applies environmental intensities at the supplier or sector level, not at the product level. Transactions are classified based on supplier SIREN identifiers and their associated NAF codes, which are then mapped to a single EXIOBASE sector. This approach assumes that all products from a given supplier share the same environmental intensity, overlooking intra-supplier product variation (Helo et al., 2024). The lack of product-level resolution not only limits the model's utility for sustainable procurement, ecolabeling, and emissions-conscious purchasing, but also hinders the identification and promotion of low-impact innovations at the product level. In addition, it constrains opportunities for joint supplier innovation, where purchasers and vendors collaborate to develop or scale more sustainable product offerings. Without visibility into specific product characteristics, organizations miss critical leverage points for driving change across value chains.

In addition, the use of broad inflation metrics such as INSEE's national Consumer Price Index (CPI) fails to reflect sector-specific pricing dynamics. Industries with divergent cost trajectories, such as energy and software, can experience significant distortions in longitudinal environmental accounting if uniform inflation adjustments are applied.

The model's spatial resolution is similarly constrained. EXIOBASE provides data only at the national level, and impact assessment tools like Impact World+ rely on global averages. This neglect of regional environmental variability reduces the model's relevance for localized planning or regional procurement strategies (Gómez et al., 2016).

Another important limitation concerns the temporal relevance of input data. EEIO databases such as EXIOBASE are typically based on economic and environmental data from past years (e.g., 2022), which may not reflect current or future sectoral dynamics, decarbonization trajectories, or technological shifts (Ozawa-Meida et al., 2013).

Additionally, EXIOBASE, while widely used for EEIO modeling in Europe, is limited in its environmental scope. For the climate change category, it focuses primarily on CO_2, CH_4, and N_2O, and does not account for other greenhouse gases or climate forcers, such as HFCs or SF_6. Moreover, it lacks broader impact categories such as toxicity, water use, or resource depletion, limiting its usefulness for comprehensive life cycle assessments beyond global warming potential (Giljum et al., 2019).

From an operational standpoint, the model's effectiveness hinges on the quality and completeness of procurement data. Challenges such as inconsistent supplier identifiers (e.g., SIREN), missing NAF codes, or reliance on custom internal taxonomies can complicate accurate sectoral mapping (Sancha Fernández et al., 2016). These issues often necessitate manual reconciliation, increasing the workload for sustainability and procurement teams.

Moreover, although the model is built using open-source Python libraries (e.g., pymrio, sentence-transformers), performing semantic mapping, matrix operations, and inflation adjustments on large datasets can be computationally intensive. This may pose accessibility barriers for smaller organizations or public entities with limited technical capacity.

I.5 Conclusion

Despite its structural limitations, the supplier-level top-down modeling framework provides a scalable and standardized foundation for environmental accounting using financial transaction data. This approach is especially valuable in procurement contexts where physical product information is missing or fragmented.

Its accuracy, however, improves significantly when procurement records contain product-level

identifiers (e.g., "€X on product Z"). In such cases, integrating EXIOBASE's product-by-product configuration enables more granular assignment of environmental intensities, better reflecting intra-supplier and intra-category variation that is often masked by sectoral averages.

This refined resolution not only enhances interpretability but also strengthens the model's strategic utility, supporting targeted supplier engagement, carbon-conscious purchasing, and more robust Scope 3 emissions accounting, particularly in data-limited environments.

To further improve the model's forward-looking value, enhancements such as sector-specific decarbonization factors, dynamic emission projections, and regular database updates are needed. These will help align impact estimates with climate transition goals and enable scenario-based planning.

Finally, this section underscores a key insight: while monetary proxies offer scalability, they must be complemented by more granular data, whether product-level financial detail or physical quantity inputs, to support actionable, reliable environmental decisions.

The next section builds on this insight by shifting from supplier-level classification to a product-level top-down model, using CPF codes and EXIOBASE's product-by-product structure. This approach addresses many of the granularity limitations identified here and offers a more precise method for modeling environmental impacts across procurement portfolios.

II. Product-Level Environmental Accounting Using a Top-Down Monetary Model

II.1 Introduction

This section builds upon the supplier-level approach presented in Section I by enhancing the granularity of environmental accounting through a shift to product-level classification. Whereas the previous model relied on supplier-level economic activity codes (e.g., NAF) and used the industry-by-industry (ixi) configuration of EXIOBASE, the current approach adopts a product-centered perspective based on the product-by-product (pxp) format of EXIOBASE. This pxp configuration provides environmental intensities at the product level rather than by economic sector, allowing for more precise allocation of impacts to specific procurement items.

The classification used for this shift is the French Classification of Products (CPF, Rev. 2.1, 2015) (INSEE, 2015), which supports more accurate assignment of environmental intensities, especially in procurement categories where multiple products may be associated with a single supplier. The methodological logic remains top-down but is adapted to process procurement data classified by products instead of supplier activities. By aligning CPF codes with the pxp structure of EXIOBASE, this model increases the resolution of environmental impact estimates without requiring physical quantity

data.

The following sections describe the technical implementation of CPF-based modeling, beginning with the structure and role of the CPF system in enabling product-level environmental accounting.

II.2 Materials and Methods

This section outlines the methodological steps used to implement product-level environmental accounting based on CPF classification. It details the structure and role of the CPF system, the semantic mapping process to EXIOBASE product categories, the integration of procurement data, and the model architecture that enables transaction-level impact allocation using top-down intensity factors.

II.2.1 From Activity-Based to Product-Based Classification: The Role of the CPF System

The French Classification of Products (CPF, Rev. 2.1, 2015) provides a standardized taxonomy for identifying goods and services within the national economy. It is fully harmonized with the European Classification of Products by Activity (CPA), ensuring interoperability with EU-wide statistical and economic datasets. CPF is structured hierarchically across six levels of increasing specificity: Level 1 (Sections): A to U; Level 2 (Sub-sections): 2-digit codes; Level 3 (Divisions): 3-digit codes; Level 4 (Groups): 4-digit codes (e.g., 0111 to 9900); Level 5 (Categories): 5-digit codes; Level 6 (Sub-categories): 6-digit codes.

In this model, Level 4 is used as the reference point for environmental accounting. It provides a functional balance between detail and usability, offering enough specificity to distinguish among major procurement items, such as IT hardware, office supplies, or construction services, while remaining compatible with EXIOBASE's product resolution and standard procurement classifications. With approximately 567 product groups, Level 4 is both comprehensive and operationally manageable for mapping and analysis. For example, CPF code 2620 ("Computers and peripheral equipment") corresponds to a common IT procurement category, while code 4211 covers "Construction of roads and motorways". These examples illustrate the level of specificity available at Level 4, allowing for meaningful differentiation among major procurement types without overwhelming complexity.

This level serves as the primary unit of classification for assigning monetary environmental intensities in the product-level top-down model, building directly on the supplier-level logic while reducing aggregation bias and improving the interpretability of results.

II.2.2 Mapping CPF Product Codes to EXIOBASE Product Categories

The mapping process used in this model builds directly on the supplier-level approach described in Section 4.A.I.2, but is adapted for product-level classification as introduced in the beginning of this section.

It enables finer alignment between procurement records and environmental intensity coefficients, particularly in categories where multiple products may fall under a single supplier or activity type.

The mapping process is structured in four main steps:

1. Translation of CPF Labels: French product descriptions are translated into English using the same MarianMT model as in Section 4.A.I to maintain compatibility with EXIOBASE product labels.
2. Semantic Embedding and Similarity Matching: Translated CPF labels and EXIOBASE product names are embedded in a shared vector space using the BAAI/bge-large-en-v1.5 model. Cosine similarity scores are calculated to identify the closest EXIOBASE product match for each CPF code.
3. Confidence Thresholding and Manual Review: Matches below a predefined similarity threshold (40 %), or those that map ambiguously to multiple EXIOBASE categories, are flagged for validation. This ensures semantic consistency and avoids misclassification, particularly in high-impact or diverse product categories.
4. Final Mapping Output: Validated CPF–EXIOBASE links are compiled into a master lookup table. Each CPF Level 4 code is now associated with a specific EXIOBASE (pxp) category, allowing automated assignment of environmental intensities (e.g., kg CO_2eq/€) in Scope 3 calculations.

This semantic mapping enables CPF-classified procurement data to be directly linked with the environmental intensity factors embedded in the EXIOBASE database, thereby supporting product-level environmental impact assessments that are both scalable and interpretable.

The calculation and extraction of environmental intensity factors from EXIOBASE in this product-level model follow the same methodological approach detailed in Section 4.A.I. As before, the process uses the pymrio Python library to load EXIOBASE data, apply characterization factors (from Impact World+), and compute environmental impacts using the Leontief demand-driven model. The key distinction here is the use of the product-by-product configuration of EXIOBASE rather than the industry-by-industry format. This allows environmental intensities to be expressed at the product group rather than by economic activity. The same inflation correction, normalization to EUR2024, and midpoint impact categories (climate change and water scarcity) are applied to ensure methodological consistency with the supplier-level model.

II.2.3 Procurement Data Integration and Classification Using CPF Product Codes

In the product-level version of the model, each procurement transaction must be classified using standardized codes. The recommended classification system is the CPF, which enables more granular allocation of environmental impacts based on the specific nature of the purchased goods or services.

While the overall modeling approach aligns with the supplier-level framework, a key distinction lies in data availability. Unlike standardized supplier identifiers (e.g., SIREN codes), CPF codes are often absent from procurement records due to reliance on internal or incompatible classification systems. This mismatch frequently necessitates manual coding, especially when product descriptions are unclear. To address this, organizations should upgrade procurement systems and workflows, such as ERP platforms, to integrate standardized product classifications like CPF (El Haouat et al., 2023). This alignment is critical for automating product-level emissions accounting and improving the reliability of Scope 3 reporting.

II.2.4 Model Architecture

The architecture of the product-level environmental accounting model parallels the structure of the supplier-level approach, with modifications to accommodate product-based classification and the use of EXIOBASE's pxp format . The workflow integrates procurement data tagged with CPF Level 4 product codes, semantically mapped to corresponding EXIOBASE categories. These codes are linked to environmental intensity factors, expressed in impact per euro of expenditure, enabling transaction-level carbon and water footprint estimates. The model maintains consistency through the same Leontief demand-driven framework used in the supplier-level version but enhances granularity by capturing intra-supplier variation. This refinement helps identify high-impact items in diversified purchasing categories where supplier-level classification can obscure environmental heterogeneity. Figure 4-3 outlines the key components and data flows in this process, from EXIOBASE data extraction and CPF classification to semantic mapping, intensity assignment, and final impact calculation and reporting. The specific changes are visually marked in blue within the diagram.

II.3 Demonstration Results

To validate the product-level environmental accounting model, we applied it to the same anonymized procurement dataset introduced in the supplier-level demonstration (Table 4-2). Each transaction was tagged with a CPF Level 4 code, enabling impact allocation based on product type rather than supplier activity. The CPF-enriched dataset was processed through the product-level modeling pipeline using the EXIOBASE pxp format, yielding detailed environmental impact estimates. For instance, Product P1, purchased from Supplier S1, and Product P2, purchased from Supplier S2, were both assigned impact values that deviated from those suggested by their respective supplier-level sector classifications. This illustrates how the product-level model can reveal environmental hotspots that are obscured when impacts are aggregated solely by supplier activity. The results, summarized in Table 4-4 and Figure 4-4, demonstrate the model’s ability to differentiate impacts across product categories and highlight high-intensity items that may not be visible under supplier-level aggregation. This perspective underscores the added granularity and analytical value of product-level Scope 3 accounting.

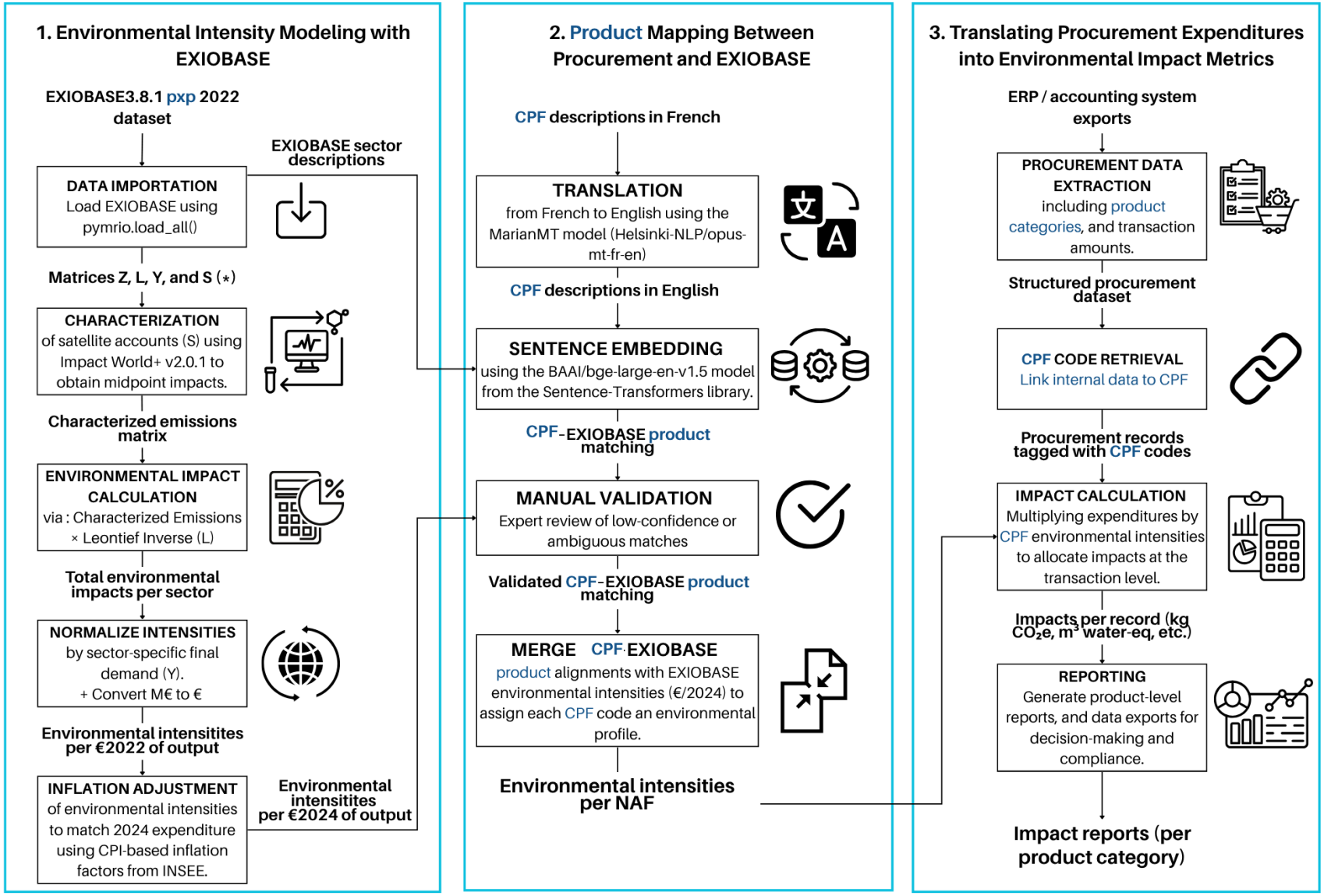


Figure 4-3 Methodological Workflow for Translating Procurement Data into Product-Level Environmental Impact Metrics

Table 4-4 Demonstration Output: Product--Level Environmental Impact Allocation Using Product-Based Intensities

	Product Category	**CPF**	**Exiobase product**	**kg CO2 eq per EUR2024**	**m3 water eq per EUR2024**	**Expenditures (EUR2024)**	**kg CO2 eq**	**m3 water eq**
P1	Medical equipment	26.60	Medical, precision and optical instruments, watches and clocks (33)	0.3549	0.2901	2000	709.767	580.205
P2	Office machinery and accessories	28.23	Office machinery and computers (30)	0.3148	0.2880	3500	1101.810	1008.098
P3	Works relating to fluid networks	42.21	Construction work (45)	0.2081	0.1904	12000	2497.063	2284.661
P4	Catering	56.10	Hotel and restaurant services (55)	0.0755	0.1232	1000	75.535	123.200
P5	Binding and related services	18.14	Other services (93)	0.0465	0.0938	500	23.273	46.884
P6	Footwear	15.20	Wearing apparel; furs (18)	0.5360	0.8289	4850	2599.762	4020.312
P7	Other specialized construction work n.e.c.	43.99	Specialized construction services n.e.c.	0.3449	0.2010	8000	2758.836	1607.647
P8	Poultry meat	10.12	Products of meat poultry	0.3015	0.6393	3980	1200.099	2544.579
P9	Electricity	35.14	Distribution and trade services of electricity	0.6839	0.2166	750	512.960	162.440
P10	Other carpentry and framework elements (Wood)	16.23	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials (20)	0.2955	0.1757	6900	2038.697	1212.560
Total						**43480**	**13517.802**	**13590.586**

II.4 Discussion

This section compares supplier-level and product-level environmental accounting models and analyzes their limitations. It focuses on how classification structures, data granularity, and input types influence the accuracy and usefulness of Scope 3 procurement impact assessments.

II.4.1 Comparative Analysis of Supplier-Level and Product-Level Environmental Accounting

The figures derived from the implementation of two top-down monetary models illustrate the environmental impact of procurement activities using two distinct classification systems: supplier-based (Figure 4-2) and product-based (Figure 4-4). Both models use the same underlying financial transaction dataset but differ in how environmental intensities are assigned.

The supplier-level model allocates emissions based on the supplier's economic activity code (NAF), mapped to sectoral emission factors in EXIOBASE's industry-by-industry (ixi) configuration. In contrast, the product-level model classifies transactions using CPF Level 4 product codes, mapped to EXIOBASE's product-by-product (pxp) format. This methodological shift allows for more refined and accurate allocation of environmental impacts, particularly in procurement categories where supplier activity and product type diverge significantly.

Expenditure distributions remain consistent across both models, as they reflect the same transaction values. Suppliers S3, S7, and S10 emerge as the top three in terms of procurement spending. However, when assessing environmental impact, particularly carbon emissions, the differences between the models become apparent. In the supplier-level model, carbon emissions are driven primarily by S3 and S10, whose sectors (e.g., construction and carpentry) are associated with high emission intensities. In the product-based model, however, the top carbon contributors shift to P7, P6, and P3, reflecting the influence of more carbon-intensive product types that may not be evident from the supplier's general sector classification alone.

The water scarcity analysis reveals a similar reordering. In the supplier-level model, S10 and S3 dominate water-related impacts due to their alignment with water-intensive sectors like wood manufacturing. However, the product-level model identifies P6 and P8 as the leading contributors to water use, with P6 far surpassing all others. This suggests that water-intensive products such as certain textiles or food-related items (associated with P6 and P8) are driving water scarcity impacts that are not visible when only supplier activity codes are used. Notably, products like P3 and P7, while still impactful, are overtaken in water scarcity by categories not emphasized in the supplier-based analysis. These findings demonstrate that while supplier-level modeling is useful for high-level screening, it can obscure critical details in procurement portfolios where product-level variability is significant.

The product-level model reveals intra-supplier differences and highlights high-impact items that are masked under sectoral averages. For example, Product P1, purchased from Supplier S1, and Product P2, from Supplier S2, both show environmental profiles in the product-level model that deviate from what their supplier sectors suggest, emphasizing the value of classification by product rather than entity.

These comparative results suggest that product-based classification improves resolution and supports better-informed decisions, especially when combined with hybrid models that flexibly apply sectoral or item-specific data based on quality and availability.

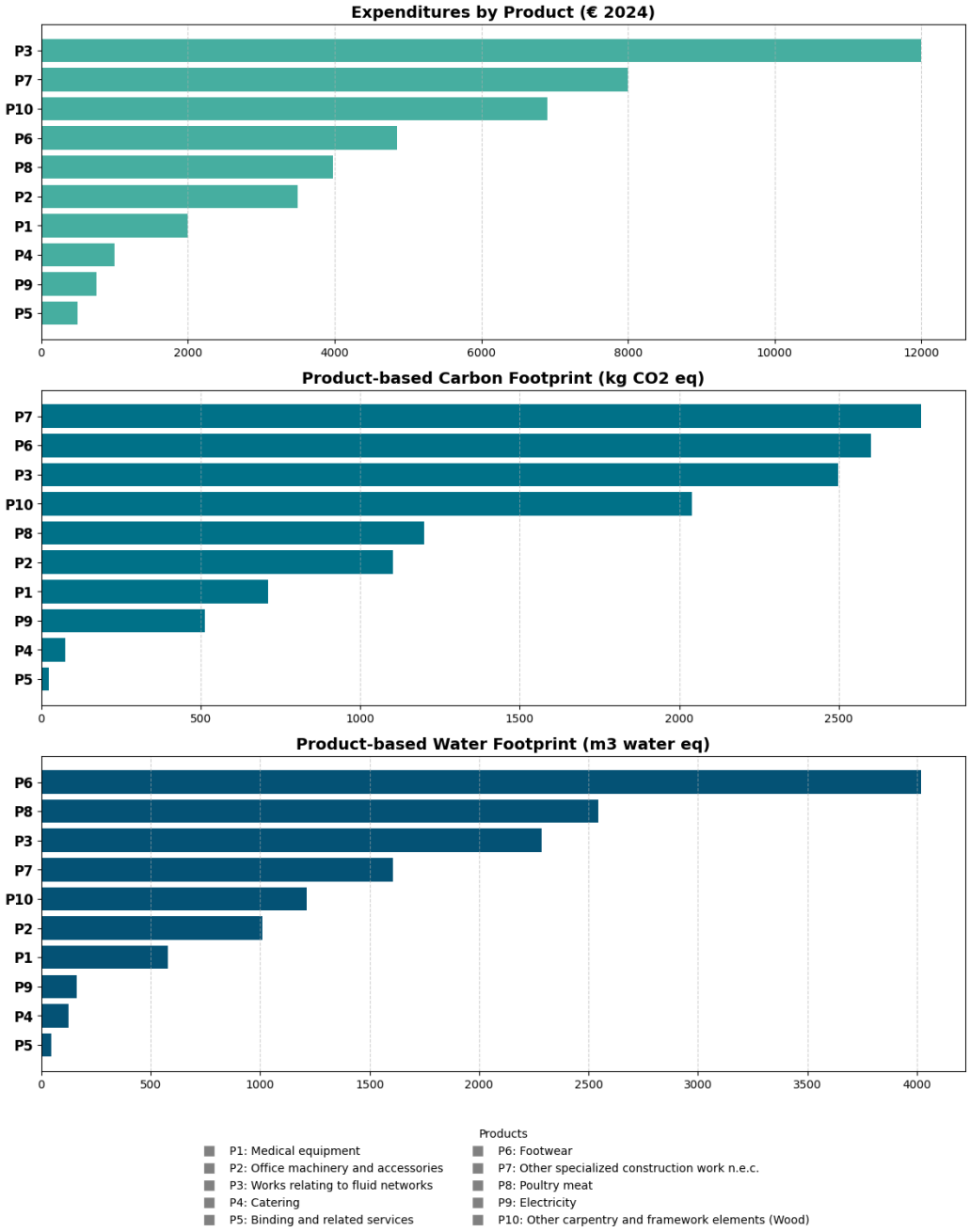


Figure 4-4 Bar Chart of Product-Level Environmental Impacts

II.4.2 Limitations of the Model and Perspectives

While the product-level top-down model offers a significant advance in environmental accounting resolution, several structural and operational limitations constrain its reliability, precision, and scalability.

One key issue is the lack of standardized product classification in procurement systems. Unlike supplier identifiers such as SIREN and NAF codes, CPF codes are rarely embedded in accounting platforms. Many organizations rely on proprietary or legacy taxonomies that do not align directly with the CPF hierarchy, necessitating manual reclassification of procurement records. This introduces interpretive overhead, limits automation, and increases the risk of inconsistency, especially when item descriptions are vague, duplicated, or incomplete (Pedersen and Remmen, 2022; Tukker and Jansen, 2006).

Semantic mapping between CPF and environmental databases like EXIOBASE further complicates the modeling process. While embedding-based techniques provide a scalable foundation, many CPF product labels are ambiguous, overly broad, or poorly defined, leading to uncertain or imprecise matches. Manual review remains necessary for low-confidence mappings, which limits scalability and introduces potential inconsistencies, particularly for high-impact, multifunctional, or novel products (Reimers and Gurevych, 2019).

A deeper structural limitation lies in the reliance on average monetary emission factors from EXIOBASE, which assumes uniform environmental performance within each product group. The model cannot differentiate between materially distinct items, such as recycled versus virgin materials, or energy-efficient versus standard equipment, if they fall under the same CPF code. This aggregation flattens product-specific variability and undermines the model's value for applications such as ecolabeling, supplier comparison, or targeted green procurement (Anastasiou et al., 2024; Nakamura, 1999).

Moreover, the exclusive use of monetary expenditure data as the input variable introduces significant distortions. Prices often reflect factors unrelated to environmental impact, such as branding, packaging, or service bundles. Even for identical products from the same supplier, prices can vary significantly between clients due to contract terms, purchasing volumes, or negotiated discounts. This intra-supplier price variability further undermines the comparability and consistency of impact estimates (Lueddeckens et al., 2022).

As a result, low-cost but high-impact items may appear less significant than high-cost but environmentally benign alternatives. Without accompanying physical quantity data, such as weight, volume, energy content, or number of units, the model risks misrepresenting actual environmental

burdens. Financial data alone is insufficient to characterize the environmental intensity of procured goods, especially in categories with high price dispersion or complex supply chains (Ding et al., 2015).

The effectiveness of the model also depends on the structure and completeness of procurement data. Missing product identifiers, inconsistent formatting, and fragmented procurement systems can disrupt CPF mapping and prevent accurate impact attribution. In many organizations, this necessitates substantial preprocessing, data cleaning, and coordination across departments, all of which add friction and reduce scalability (Agrawal et al., 2025).

Finally, while the model improves resolution relative to supplier-level approaches, it remains a monetary proxy system. It does not account for supplier-specific practices, regional supply chain differences, production technologies, or verifiable environmental disclosures. Without the integration of bottom-up physical data, such as that from process-based life cycle inventories (e.g., ecoinvent) or supplier-issued declarations (e.g., EPDs), the model cannot capture the full variability or specificity of upstream emissions.

These findings reinforce the need to complement monetary proxies with physical data inputs, such as mass, volume, or energy content, to improve specificity, comparability, and methodological robustness. This integration sets the stage for hybrid models that combine the scalability of top-down systems with the rigor of process-based inventories.

III.5 Conclusion

This section introduced and implemented a product-level top-down environmental accounting model that improves upon supplier-level approaches by using CPF codes and EXIOBASE's product-by-product (pxp) format to estimate Scope 3 emissions. By aligning procurement transactions with CPF Level 4 codes and linking them to pxp-based environmental intensity factors, the model achieves a more refined representation of procurement-related impacts, particularly for carbon and water.

The demonstration results show that product-level classification captures intra-supplier variability and highlights high-impact procurement items that remain hidden under sectoral averages. This granularity improves the interpretability of results and supports more targeted sustainability decisions. It also enables more flexible hybrid modeling approaches that combine sectoral and item-specific data depending on availability and reliability.

However, the analysis also reveals key limitations. The model relies on financial data, which alone cannot represent environmental intensity with sufficient accuracy, especially in cases of high price dispersion or heterogeneous product content. It also depends on standardized procurement classification (CPF), which is often absent or inconsistently used in organizational ERP systems.

Semantic mapping between CPF codes and EXIOBASE categories remains fragile and frequently requires manual validation. Additionally, the use of average monetary emission factors cannot reflect critical differences in material origin, production technology, or supplier-specific practices (Lenzen, 2000).

These findings underscore a central insight: monetary data, even when finely classified, cannot fully capture the complexity of environmental impacts embedded in procurement. To overcome this constraint, organizations must integrate physical data, such as weight, volume, energy content, or unit count, to enable more robust environmental footprinting. Doing so allows for direct linkage to process-based life cycle inventory (LCI) databases and supports the transition toward hybrid models that combine the scalability of top-down approaches with the precision of bottom-up methods.

Ultimately, achieving meaningful Scope 3 accounting at the product level requires more than technical modeling. It depends on procurement system modernization, structured data practices, and cross-departmental collaboration (Busse et al., 2016). By embedding standardized product classification and enabling integration with environmental databases, organizations can move toward scalable, automated, and decision-relevant sustainability reporting.

III. Product-Level Environmental Accounting Using Bottom-Up Physical Data

III.1 Introduction

This section introduces a bottom-up, physically grounded approach to product-level environmental accounting, designed to address the limitations of the top-down monetary models presented in Sections I and II. While monetary methods rely on average emission intensities per euro of expenditure, the bottom-up model shifts the focus to empirical, material-based indicators, assigning environmental burdens based on the physical characteristics of procured goods, such as mass, volume, surface area, energy content, or item count.

Grounded in process-based LCA methodologies, this approach utilizes standardized LCI data from reputable databases such as ecoinvent and Agribalyse, supplemented where appropriate by Base Empreinte® (ADEME) for emission factor-based estimates, as well as peer-reviewed LCA studies and EPDs. Environmental impacts are calculated per functional unit (e.g., kg CO_2eq/kg, m^3 water/ number of unit), allowing for more accurate and differentiated assessment of products based on material composition, production processes, geographic origin, and performance attributes (Backes et al., 2023). This is especially critical in high-impact procurement categories, such as construction, agriculture, and energy, where price often fails to reflect environmental intensity (Ritchie, 2020).

By moving beyond monetary proxies, the bottom-up model enables meaningful differentiation between low- and high-impact variants of similar products (e.g., recycled vs. virgin aluminum, energy-

efficient vs. conventional appliances), supports supplier-specific evaluation, and fosters collaborative innovation within the supply chain (Shan et al., 2020). Rather than focusing solely on material substitution, this approach enables organizations to engage with suppliers in the co-development of lower-impact solutions, promoting continuous improvement in product design, sourcing, and manufacturing processes (Styles et al., 2012). It also provides a robust foundation for integrating EPDs, Product Environmental Footprints (PEFs), and emerging traceability tools, aligning with evolving regulatory requirements (e.g., CSRD).

Importantly, this approach is intended not as a replacement but as a complementary component within a hybrid modeling framework. It can be selectively applied where reliable physical data are available, while top-down monetary models remain useful for broad screening or less material-intensive categories. This tiered strategy balances scalability and precision, enhancing the robustness of Scope 3 procurement-based environmental accounting.

The following sections detail the data requirements, methodological workflow, and demonstration results of the bottom-up model, highlighting its comparative advantages and strategic applications.

III.2 Materials and Methods

This section outlines the data requirements, organizational conditions, and methodological steps used to implement the bottom-up environmental accounting model, with a focus on linking procurement records to life cycle inventory data for Scope 3 impact estimation.

III.2.1 Data Requirements and Organizational Readiness

Implementing a bottom-up model necessitates a structured and comprehensive dataset encompassing both physical procurement attributes and standardized environmental impact coefficients. Core data components include:

- Quantitative metrics: Mass (kg), volume (L or m^3), surface area (m^2), energy content (kWh), or number of units.
- Product identifiers: Harmonized CPF Level 4 codes, or internal classification schemas cross-referenced to external LCI datasets.
- Material and product specifications: Documentation describing the material composition, intended use, and production characteristics of procured goods (e.g., energy source, manufacturing process…).
- Source of environmental impact factors: Credible and peer-reviewed databases such as ecoinvent, Agribalyse, Sphera, Base Empreinte® (ADEME) or relevant EPD repositories, specifying impact per physical unit.

Organizational readiness hinges on the capacity to collect, standardize, and process these data types. This often requires integration across procurement, product and material inventory, and sustainability departments, and may entail enhancements to existing ERP systems or adoption of product data management tools (Anaya and Qutaishat, 2022). Where raw descriptions are unstructured, natural language processing (NLP) and AI techniques can be used to extract material and quantity information semi-automatically (Schöpper and Kersten, 2021).

III.2.2 Methodological Steps for Environmental Impact Allocation and Model Architecture

The bottom-up environmental accounting model follows a structured, data-driven workflow that translates procurement records into product-level environmental impact estimates. The process comprises eight interconnected stages, as illustrated in Figure 4-5:

1. Procurement Data Extraction: Structured data is exported from ERP or accounting systems, including product descriptions (in French), quantities, and metadata such as supplier information or internal cost codes.
2. Translation: Product descriptions are translated to English (if needed) using a machine translation model (e.g., MarianMT).
3. Classification: The translated descriptions are then classified using CPF Level 4 or equivalent product codes to enable standardized categorization.
4. Functional Unit Definition: For each classified product category, an appropriate physical unit is assigned (e.g., kilograms, cubic meters, kilowatt-hours). This unit serves as the basis for environmental impact factor matching and allocation.
5. Manual Matching & LCI Data Retrieval: Classified products are manually mapped to representative LCI processes using product details, material specifications, and functional units. Relevant environmental impact factors (e.g., kg CO_2eq per kg, m^3 water per m^2) are calculated from established sources such as ecoinvent, Agribalyse, or EPD repositories. Geographic relevance and methodological alignment guide selection.
6. Impact Factors Calculation via LCIA: To translate LCI flows into environmental impacts, LCIA methods such as Impact World+ are applied. This involves multiplying the LCI flows (e.g., emissions, resource use) by corresponding characterization factors defined by the LCIA method to calculate impact factors (e.g., kg CO_2eq, m^3 water use). LCIA enables the quantification of environmental impacts across multiple categories, providing a standardized basis for comparison and decision-making.
7. Impact Calculation: Environmental impacts are computed by multiplying the physical quantity of each product by its corresponding intensity factor (Equation 4-3). This yields absolute impact values for each record:

$$\boldsymbol{Impact}\ (\boldsymbol{e.g.}, \boldsymbol{CO_2e}) = \boldsymbol{Quantity}\ (\boldsymbol{e.g.}, \boldsymbol{kg}) \times \boldsymbol{Impact\ Factor}\ (\boldsymbol{e.g.}, \boldsymbol{kg\ CO2e/kg\ or\ m^3}\ \ldots)$$

Equation 4-3 Environmental Impact Calculation Using Intensity Factors

8. Reporting and Aggregation: The resulting impact data is aggregated by product category, supplier, or organizational unit and formatted into reports for internal decision-making or external compliance (e.g., CDP, CSRD, GHG Protocol). Outputs include impacts per product category in units such as kg CO_2eq and m^3 water-eq.

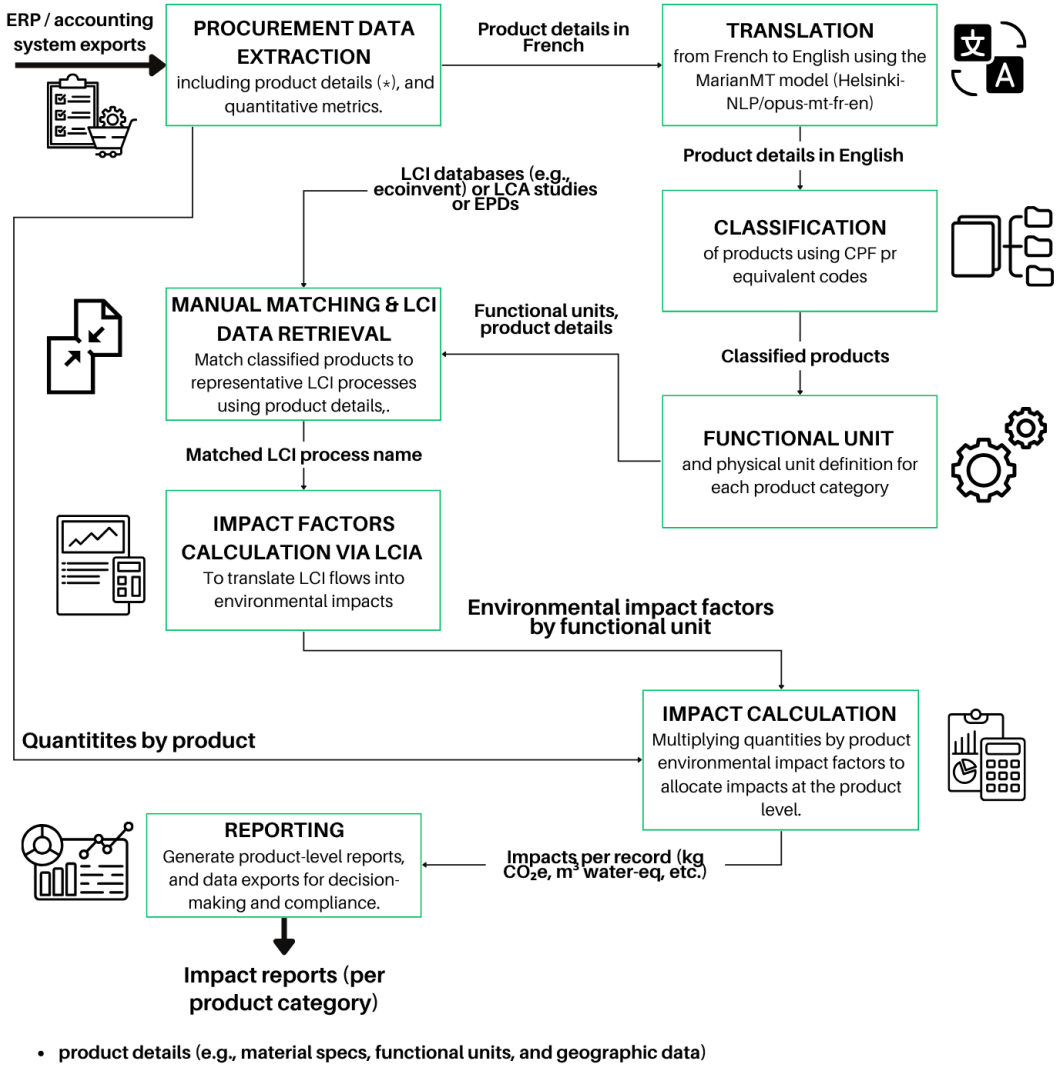


Figure 4-5 Workflow for Bottom-Up Environmental Impact Allocation Using Product-Level Procurement Data

In the bottom-up environmental accounting model, assigning environmental impact factors to procured products requires precise linkage between product records, typically classified via CPF codes or free-text descriptions, and representative processes in LCI databases such as ecoinvent, Agribalyse, or Base Empreinte® (ADEME). While semantic embedding methods have shown value for sector-level classification in top-down modeling, their application to bottom-up, process-level matching introduces significant challenges, which are discussed later in this section.

III.3 Demonstration Results

The procurement dataset employed in this bottom-up analysis corresponds to the same set of transactions introduced in Table 4-2, previously used in the top-down supplier-level (Model I) and product-level (Model II) environmental accounting frameworks. While top-down models estimate environmental impacts based on monetary expenditures and sectoral or product classification codes, the bottom-up model integrates physical quantity data with process-specific emission factors derived from detailed LCI databases or LCA studies. This shared dataset foundation enables consistent comparison of results across modeling tiers.

Table 4-5 presents ten representative procurement items analyzed using the bottom-up framework, detailing each product's specification, unit of measurement, estimated quantity procured, and associated environmental impacts in terms of total carbon footprint (kg CO_2 eq) and water scarcity (m^3 water eq). It also includes the corresponding Life Cycle Inventory (LCI) process, geographic origin, and data source. This bottom-up assessment reveals significant variation in total environmental impacts across product categories, contrasting with the more aggregated and averaged results typically seen in top-down models, thus underscoring the essential role of combining physical quantity data with process-specific LCI factors to achieve more accurate and detailed Scope 3 emissions accounting.

III.3.1 Carbon Footprint Analysis

The comparative analysis of carbon footprint estimates across Models I (top-down supplier-level), II (top-down product-level), and III (bottom-up physical data) reveals significant discrepancies, underscoring the inherent limitations of monetary-based top-down approaches (Figure 4-6).

Notably, Model III often produces significantly different emission estimates, either higher or lower, compared to other models, particularly for procurement items characterized by complex supply chains or process-intensive production. For example, acrylic binding services (P5) exhibit over 300% greater emissions in the bottom-up model compared to top-down estimates, highlighting the inability of aggregated sectoral factors to capture process-specific impacts accurately. Conversely, certain products, such as raw chicken breast (P8) and excavation services (P7), show substantial underestimation by top-down models, with differences exceeding 90%, reflecting the enhanced resolution afforded by physical quantity data in bottom-up modeling. However, for standardized products like medium voltage electricity (P9), all models converge closely, indicating that top-down approaches may suffice when product variability and procurement complexity are minimal. For P3 (Water works construction) and P4 (Pizza with landons onions and cheese), the differences across models are minimal, below 5%, suggesting that either modeling approach can deliver consistent results when product definitions are clear and data structures are relatively uniform.

Table 4-5 Bottom-Up Environmental Impact Estimates of Representative Procurement Items with Corresponding LCI Processes and Geographic Origin

	Product specifications	**Unit**	**Estimated units**	**kg CO2 eq**	**m3 water eq**	**Process**	**Location**	**Data source**
P1	PTFE-Nitinol Guidewire with a hydrophilic tip	# of item	400	423.48	179.68	vascular imaging guidewires or snares or accessories, PTFE-Nitinol Guidewire with Hydrophilic Tip	RER	adapted from (Cimprich and Young, 2023)
P2	Toner module for laser printer, black/white	# of item	15	215.034	65.806	market for toner module, laser printer, black/white	GLO	ecoinvent 3.10
P3	Water works construction	# of item	300	2408.31	1020	water works construction, capacity 1.1E10l/year, microstrainer treatment	RER / CH	ecoinvent 3.10
P4	Pizza with lardoons onions and cheese	kg	33.33	75.167	90.167	Pizza, lardoons onions and cheese, processed	FR	Agribalyse
P5	Acrylic binding service	# of item	600	5.73	3.246	laminating service, foil, with acrylic binder	RER	ecoinvent 3.10
P6	Leather shoes imported from China	# of item	108	463.44	Not available	consumer_goods-type_leather_shoes	CN	Chinese Academy of Environmental Planning (CAEP)
P7	Excavation by skid-steer loader	m3	100	578.6	21.2	excavation, skid-steer loader	RER	ecoinvent 3.10
P8	Raw chicken breast	Kg	350	1666	1847.65	chicken, breast, meat and skin, raw	FR	Agribalyse
P9	Medium voltage electricity	KWh	7000	539.7	932.4	electricity, medium voltage	FR	ecoinvent 3.10
P10	Softwood for carpentry	m3	34.5	2294.87	1096.134	sawnwood production, softwood, dried (u=10%), planed	RER / CH	ecoinvent 3.10

Legend: Location codes indicate the geographic scope of LCI processes: RER = Rest of Europe; FR = France; CH = Switzerland; CN = China; GLO = Global average; RER / CH = Rest of Europe excluding Switzerland

In accordance with Wiedmann (2009) and Nicholls et al. (2015), these findings illustrate that while top-down models offer scalability and ease of implementation, integrating bottom-up data is critical to improve accuracy and identify emissions hotspots within procurement portfolios, thereby supporting more targeted and effective sustainability interventions.

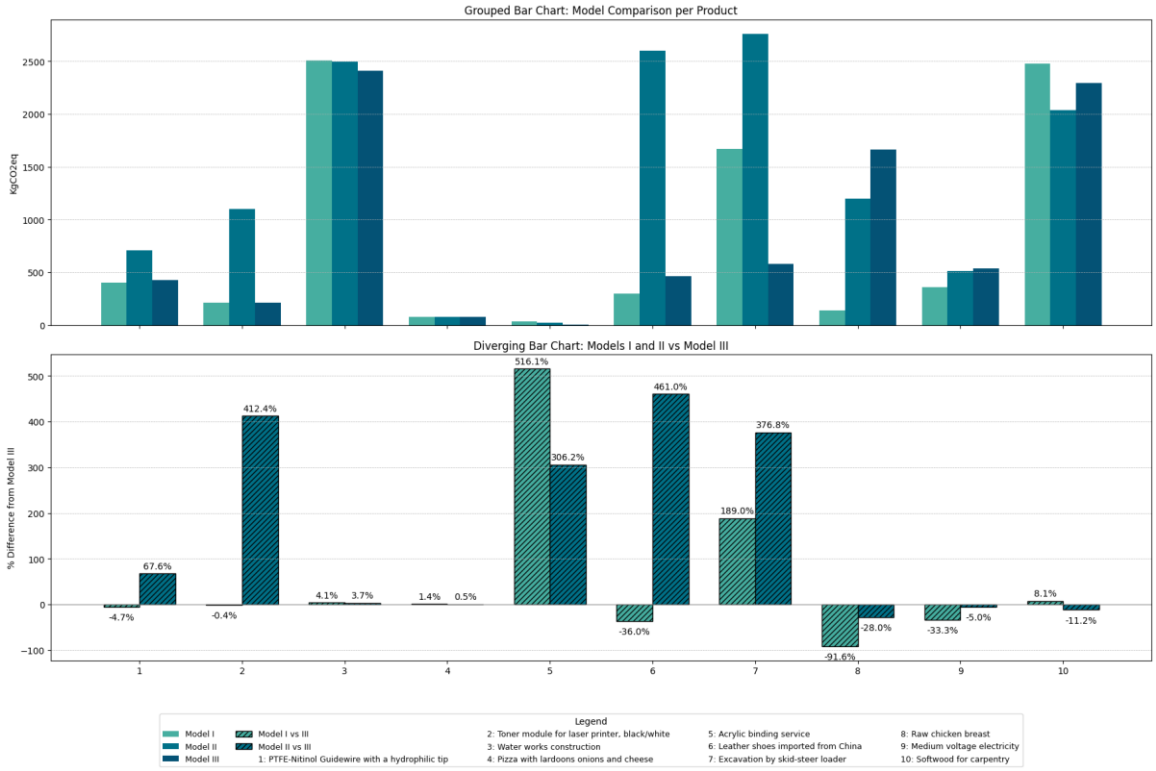


Figure 4-6 Carbon Footprint of Procurement Items Based on Bottom-Up Modeling

III.3.2 Water Scarcity Analysis

The comparison of water scarcity impact estimates across Models I (top-down supplier-level), II (top-down product-level), and III (bottom-up physical data) reveals pronounced discrepancies that highlight the challenges of accurately capturing water impacts in procurement accounting (Figure 4-7).

The bottom-up model (Model III) consistently estimates significantly higher water scarcity impacts for several products, especially those related to agriculture and food supply chains. For example, pizza with lardoons onions and cheese (P7) shows an extraordinary increase of over 7,400% relative to Model I and over 3,200% relative to Model II, underscoring the limitations of monetary-based sector averages in reflecting water scarcity embedded in complex food production processes. Similarly, water works construction (P3) and acrylic binding service (P5) exhibit differences exceeding 1,300%, further illustrating the underestimation of water consumption in top-down frameworks for process-intensive goods and services. These discrepancies may also stem from the implementation of Impact World+ and its regionalized characterization factors in ecoinvent, or from issues related to water flow modeling and inventory allocation.

Conversely, products such as raw chicken breast (P8) demonstrate negative percentage differences, indicating that some top-down estimates may exceed bottom-up assessments, potentially due to overgeneralization or data inconsistencies within EEIO datasets. Other items, like medium voltage electricity (P9) and softwood carpentry (P10), show moderate divergence, with top-down models underestimating water scarcity impacts by 75–85%, reflecting incomplete capture of water use during material processing.

Data for leather shoes imported from China (P6) was not available for water scarcity assessment, indicating a gap in current datasets for certain global supply chains. This absence highlights the need for expanded and regionally detailed physical data to improve procurement water impact accounting.

Overall, these findings emphasize the critical importance of integrating bottom-up physical data to capture the true scale of water scarcity impacts associated with procurement. The substantial variation between models underscores the risk of relying solely on monetary proxies and supports the development of hybrid approaches that combine the scalability of top-down models with the precision of bottom-up data to enhance water stewardship and sustainability decision-making (Gamarra et al., 2023).

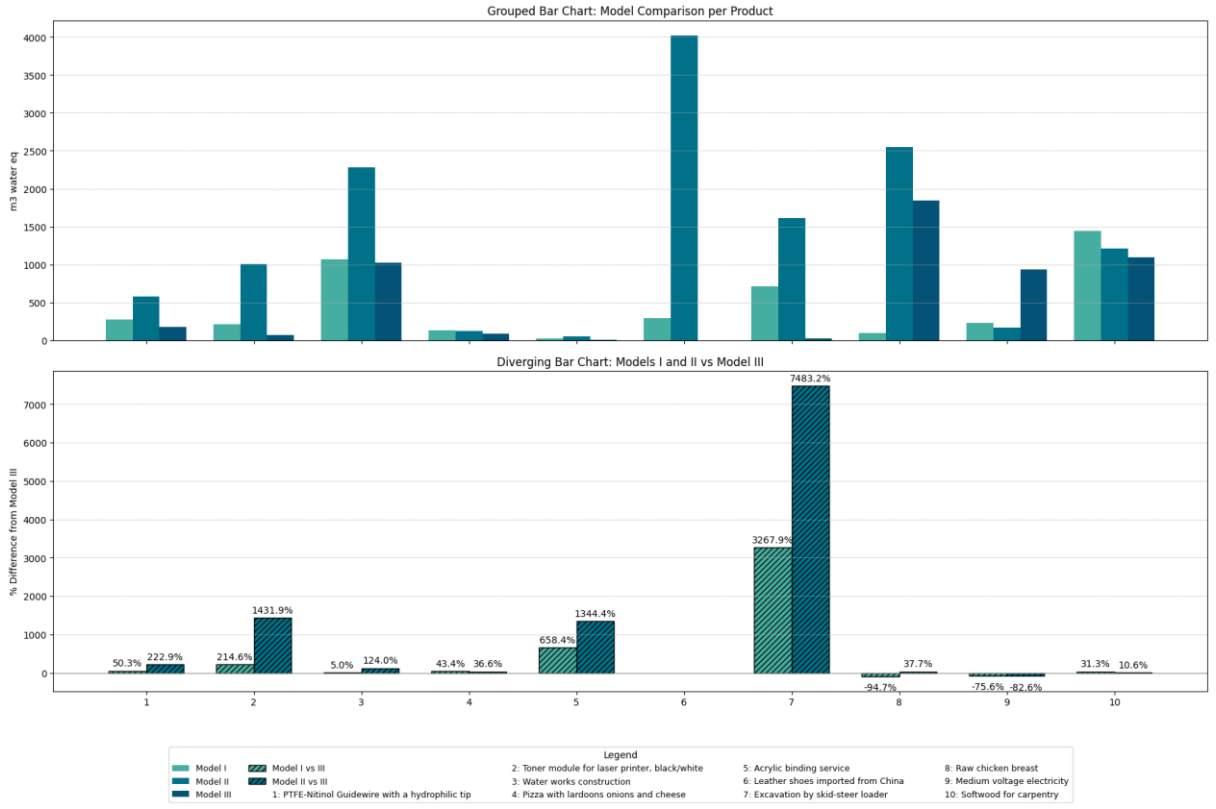


Figure 4-7 Water Scarcity of Procurement Items Based on Bottom-Up Modeling

III.3 Discussion

The demonstration and implementation of the bottom-up environmental accounting model revealed several structural and technical limitations that constrain its scalability and accuracy. This section discusses practical barriers to fully automated environmental assessments observed during the demonstration phase. It highlights two interconnected challenges:

III.3.1 Limitations of LCI Databases and the Imperative for Supplier-Specific Data

Bottom-up environmental accounting offers higher accuracy and granularity than top-down methods, but its practical application is constrained by fragmented data sources, inconsistent procurement system integration, and limited access to verified supplier-level information (Balcioglu et al., 2025). This section addresses the challenges posed by heterogeneous LCI databases, the growing need for standardized supplier data, and the critical role of procurement system integration.

One of the core issues lies in the inconsistencies among major LCI databases such as ecoinvent, Agribalyse, Base Empreinte® (ADEME), and Sphera. These datasets differ across four key dimensions (Montemayor et al., 2022; Steubing et al., 2016):

- System boundaries, ranging from cradle-to-gate to cradle-to-grave, which drastically affect impact results.
- Geographic coverage, with some datasets reflecting national averages and others offering global or regional data, often mismatched with actual sourcing locations.
- Temporal resolution, where outdated or aggregated data may not capture recent technological or regulatory changes.
- Process granularity, as many entries group distinct production methods under generic labels, making it hard to select an appropriate match.
- Allocation rules, which define how environmental burdens are distributed among co-products or by-products and can significantly influence the comparability of results across databases (e.g., economic vs. mass-based allocation).

Furthermore, recent findings from CEA and BRGM (2023), in the context of assessing carbon footprint rules for electric vehicle batteries, indicate that ecoinvent significantly underestimates the environmental impacts of several key metals. This raises concerns about the database's suitability for modeling high-impact supply chains, particularly in sectors reliant on critical raw materials. This inconsistency undermines comparability and trust, especially in regulatory or disclosure contexts (Teng et al., 2023).

Choosing an appropriate dataset involves trade-offs between local relevance, international comparability, and regulatory alignment, and often requires expert judgment. While this diversity

reflects different use cases and data collection methods, it complicates integration and introduces uncertainty unless managed through a structured approach (Ciroth, 2021).

III.3.2 Operational Challenges in Matching Procurement Data with LCI Inventories

Based on the application of the model in the procurement context and the iterative development of the bottom-up matching code, several limitations were identified that hinder full automation and require methodological adjustments.

One of the primary barriers is semantic under-specification in CPF and procurement records. Labels such as “binding and related services” often lack the necessary detail, such as material type, additive content, or production technique, to distinguish between processes with significantly different environmental profiles (Bauld, 2022). Embedding models, which rely on surface-level linguistic similarity, are unable to infer such latent distinctions, leading to misclassification. Unlike economic sector classifications, which are relatively broad and descriptive, LCI process names encode detailed information about material type, transformation methods, regional applicability, and system boundaries. This complexity exceeds the generalization capacity of standard semantic embedding models, particularly those not trained on domain-specific data. Despite high similarity scores, embedding-based methods often failed to return functionally valid matches when applied to granular CPF entries or short procurement descriptions. This was especially evident in product categories such as building materials, and electrical equipment, where environmental impacts can vary significantly based on composition, manufacturing route, or supply chain attributes, due to differences in energy intensity, raw material sourcing, and supplier-specific practices (EEA, 2021).

A second limitation lies in the absence of unit-aware matching. Bottom-up modeling requires correspondence between a physical quantity (e.g., kilograms, square meters) and an environmental intensity per functional unit (e.g., kg CO_2eq/kg). Embedding models treat all inputs as plain text and lack the ability to reason over measurement units, scale, or quantity-based context. This introduces systematic uncertainty, particularly for products where the same label could correspond to multiple LCI processes depending on the unit of analysis.

Additionally, LCI datasets often include process naming conventions and metadata structures that do not align naturally with CPF or procurement descriptions. For instance, process names may begin with qualifiers such as "market for" or contain geographic references (e.g., "at plant, CH"), which may confuse or bias automated similarity rankings unless explicitly filtered (Wernet et al., 2016). These structural differences further degrade the utility of direct semantic alignment in bottom-up modeling.

Due to these constraints, the final implementation of the bottom-up framework relied mainly on manual process matching. Each product was reviewed and matched to a representative LCI process based on available information.

While labor-intensive, this approach ensured that environmental intensities were appropriately grounded in the physical and functional characteristics of the procured goods. It also highlighted the importance of structured product metadata, such as harmonized CPF classification, unit standardization, and supplier documentation, in enabling more automated and accurate bottom-up modeling.

These findings emphasize that scalable bottom-up modeling depends not only on better data inputs, but also on smarter algorithms and more interoperable system architectures.

III.4 Conclusion

In conclusion, the research demonstrates both the potential and current constraints of applying bottom-up environmental accounting to procurement data.

Ultimately, procurement integration is not just a technical upgrade, it is a structural requirement. Without aligning what organizations buy with how they measure environmental impact, bottom-up models will remain siloed, manual, and difficult to scale. Addressing LCI fragmentation, improving supplier data availability, and embedding environmental standards into procurement workflows are essential to making Scope 3 accounting reliable, scalable, and decision-ready.

To improve precision, many organizations are increasingly turning to primary data from suppliers, including: PCFs compliant with ISO 14067 or the PEF method, EPDs aligned with EN 15804 or ISO 14025, Supplier sustainability disclosures, such as CDP responses or ESG reports. These datasets offer better specificity, regional relevance, and transparency than generic LCI values.

Scaling this approach requires systematic, standards-driven collaboration with suppliers, including:

- Adoption of harmonized product identifiers (e.g., CPF, HS, UNSPSC),
- Use of interoperable data formats (e.g., ILCD+EPD, JSON-LD, XML, EcoSpold),
- Participation in digital product passport initiatives (e.g., under the EU Green Deal),
- Integration with procurement platforms and carbon accounting tools via APIs or EPD libraries.

Embedding supplier data into procurement workflows allows for more continuous, automated, and verifiable accounting, shifting away from one-off assessments to real-time Scope 3 monitoring.

However, this transformation is only possible if procurement systems evolve. Current ERP platforms are optimized for financial data, not environmental metrics (Anaya and Qutaishat, 2022). They typically

lack unit-aware quantity fields, structured material metadata, or the ability to store linked environmental documents like PCFs or EPDs. As a result, matching procurement data with LCI sources still requires manual, time-intensive work.

Where procurement data is structured and standardized, using product codes, units, and metadata, automation is achievable through NLP tools, rule-based matchers, and API integration. But such solutions are fragile when applied to vague or inconsistent inputs, especially in sectors like construction, custom goods, or professional services (Schöpper and Kersten, 2021).

To scale bottom-up accounting effectively, financial accounting and procurement systems must become enablers, not bottlenecks (Naro and Rambaud, 2023). They should capture environmental attributes at the point of purchase, embed product-level classifications, and support data exchange with sustainability systems. This calls for deeper integration between procurement, inventory, and sustainability functions, and alignment with external standards and data ecosystems.

Together, these findings point to the need for improved data infrastructures and more intelligent matching systems to unlock the full potential of product-level environmental accounting in procurement contexts. Overcoming semantic and structural limitations will require domain-specific tools, including fine-tuned embedding models, hybrid matchers with rule-based filters, and semantic ontologies from LCA standards. Until such tools mature, bottom-up modeling will continue to rely on manual or semi-automated processes to ensure methodological rigor. Integration, automation, and supplier engagement are therefore central to realizing scalable and decision-ready Scope 3 accounting. Integration, automation, and supplier engagement are therefore central to realizing the full potential of product-level environmental accounting.

IV. Integration of Supplier-Specific Data

Amid growing demands for environmental transparency, supplier-specific data is rapidly transforming from a niche consideration into a foundational element of sustainable procurement (Lu, 2024). Its integration marks a shift in how organizations understand and manage the environmental impacts embedded in their supply chains. This section outlines the key concepts, data types, and practical pathways for embedding supplier-level insights into procurement and environmental accounting systems.

IV.1 The Strategic Importance of Supplier-Specific Data

The integration of supplier-specific environmental data represents a critical evolution in procurement-based environmental accounting (Vörösmarty and Dobos, 2020). While top-down models based on sectoral or product-level averages offer broad scalability, they remain constrained by their reliance on generalized assumptions and proxy-based emission intensities. Even bottom-up models that utilize

physical quantity data, when paired with impact factors from generic LCI databases, are ultimately grounded in standardized, representative processes. Based on our own application of the model, we observed that although these approaches improve resolution relative to monetary proxies, they still fail to capture the empirical variability of specific supply chains, production practices, or supplier-level environmental performance.

From a methodological perspective, the use of primary data aligns with the core principles of LCA, which emphasize representativeness, transparency, and specificity. Supplier-specific information, such as PCFs, EPDs, or GHG inventories, captures heterogeneity in production technologies, energy sourcing, and supply chain configurations that sectoral or product-level averages necessarily obscure (Zheng and Wen, 2024). These data sources provide site- or process-specific measurements that reflect actual operational conditions, material inputs, and geographic contexts, offering a more accurate, differentiated, and decision-relevant representation of environmental impacts. This added resolution is particularly critical in procurement categories with high environmental intensity or product diversity, such as construction, electronics, and food, and is essential for organizations seeking to move beyond proxy-based estimations toward verifiable accounting and targeted emissions mitigation (Hettler and Graf-Vlachy, 2024).

The strategic value of supplier-specific data extends beyond methodological precision. In an increasingly regulated and climate-conscious economic environment, organizations face growing pressure to quantify, disclose, and mitigate their Scope 3 emissions with greater accuracy and accountability (Kim and Chai, 2017). Regulatory frameworks such as the CSRD, and evolving EU Taxonomy criteria require detailed tracking of environmental performance across supply chains. Similarly, voluntary initiatives like SBTi and the CDP emphasize supplier engagement as a core component of credible decarbonization strategies (SBTi, 2024a).

Supplier-specific data also supports the operationalization of sustainable procurement practices. By revealing intra-sectoral differences in environmental performance, such data enables organizations to move beyond risk-based screening toward proactive supplier selection, product substitution, and contract negotiation strategies based on quantified sustainability criteria. This creates a pathway for environmental differentiation in procurement, allowing firms to reward low-carbon suppliers, negotiate improved environmental performance, or co-invest in cleaner technologies (Patil et al., 2022). Moreover, sharing accurate emissions and performance data fosters joint innovation within supply chains, allowing companies and suppliers to collaborate on low-carbon product development, process improvements, and circular design solutions (Stenzel and Waichman, 2023).

Furthermore, the increasing availability of digital tools, such as EPDs accessible via standardized APIs,

product-level sustainability certifications, and blockchain-based traceability solutions, offers new mechanisms for integrating supplier data into enterprise procurement workflows (Saberi et al., 2019; Uhlhorn et al., 2024). This convergence of data availability, digital infrastructure, and regulatory demand underscores the growing strategic relevance of supplier-specific environmental accounting.

However, the integration of such data is not without challenges. Supplier participation remains uneven, particularly among small and medium-sized enterprises (SMEs), and the quality, granularity, and verification of disclosed data vary considerably. As such, the effective use of supplier-specific data requires not only technical infrastructure but also a strategic framework for supplier engagement, data governance, and incremental integration, topics addressed in the subsequent sections (Lintukangas et al., 2023).

Overall, supplier-specific data represents both a methodological enhancement and a strategic asset in the pursuit of accurate, credible, and actionable environmental impact assessment in procurement. Its integration is central to achieving high-resolution Scope 3 accounting and enabling organizations to meet emerging standards of environmental responsibility and transparency.

To operationalize the integration of supplier-specific information, it is necessary to first understand the types of environmental data suppliers can provide and how these datasets differ in terms of granularity, scope, and applicability within procurement-based accounting systems.

IV.2 Typology of Supplier-Specific Environmental Data

Supplier-specific environmental data can be broadly categorized based on the level of analysis (product, organizational, or transactional), the methodological basis (e.g., LCA, corporate inventory), and the degree of verification. Recognizing this typology is essential for integrating diverse data sources into hybrid modeling frameworks and for guiding procurement teams in evaluating data quality and relevance.

Product-Level Disclosures

At the highest level of specificity, product-level disclosures provide environmental impact estimates for a defined good or service, typically expressed per functional unit (e.g., kg CO_2eq per kilogram, m^3 water per m^2). These include:

- **Product Carbon Footprints (PCFs):** Quantify the GHG emissions associated with a product's life cycle, generally conforming to ISO 14067 or the GHG Protocol Product Standard (WRI and WBCSD, 2011b).
- **Environmental Product Declarations (EPDs):** Standardized LCA-based disclosures compliant with ISO 14025 (2006) and, in the construction sector, EN 15804 (2019). EPDs typically cover

multiple environmental impact categories (e.g., climate change, acidification, eutrophication) and specify system boundaries, geographic scope, and data sources.

- **Product Environmental Footprints (PEFs):** Developed by the European Commission as EU-recommended LCA based-based method to quantify the environmental impacts of a product, PEFs offer a harmonized methodology for multi-impact product assessment, aiming to support EU environmental labeling and procurement initiatives.

Product-level disclosures are the most informative for procurement decisions, enabling comparison of environmental performance between competing products and suppliers. However, their availability remains uneven, and verification levels vary across sectors and jurisdictions.

Organizational-Level Disclosures

Organizational-level data reflect the aggregate environmental performance of a supplier, typically reported on an annual basis. These may include:

- **Corporate GHG inventories:** Disclosures of Scope 1 (direct emissions), Scope 2 (purchased energy), and Scope 3 (value chain emissions) in accordance with the GHG Protocol Corporate Standard (2011a) or ISO 14064 (2018).
- **Carbon intensity ratios:** Metrics such as kg CO_2eq per euro of revenue, reflect emissions relative to overall business activity rather than specific products, and can be used as proxy emission factors when product-level data is unavailable (Denise, 2024).
- **Sustainability reports and ESG disclosures:** Broader narratives or datasets often aligned with frameworks like CDP, TCFD, or GRI, which may include environmental performance indicators relevant to procurement.

While less granular than product-level data, organizational-level disclosures are useful in supplier screening, performance benchmarking, and supplier-specific top-down modeling approaches. They are especially valuable when product portfolios are homogeneous or when supplier-wide averages serve as the only available data.

Transactional and Batch-Level Disclosures

Some suppliers, particularly in logistics, construction, and energy-intensive sectors, are beginning to provide transaction-specific environmental data, which reflect the actual impact associated with a given delivery or service instance (Diebel et al., 2024; Sancha Fernández et al., 2016). Examples include:

- **Batch-Specific Carbon Footprints and Certificates of Origin:** Include documentation on the carbon intensity of a particular shipment or production batch, often indicating energy source, renewable content, or regional emissions factors.

- **Transport-Related Disclosures:** Capture distance traveled, mode of transport, vehicle type, and load factor, variables that enable more accurate modeling of logistics emissions, especially in construction and distribution-heavy procurement categories.
- **Third-Party Verified Environmental Attributes:** Data such as green electricity content, bio-based material share, or certified production practices tied to invoice-level information or lot numbers.

Although not yet widespread, these disclosures can support real-time Scope 3 accounting estimation when integrated into enterprise systems, offering substantial added value where variability in delivery methods or geographic sourcing is environmentally material.

IV.3 Mapping Disclosure Types to Modeling Approaches

The integration of supplier-specific data into procurement-based environmental accounting must be aligned with appropriate modeling approaches to ensure both methodological consistency and practical feasibility. Product-level disclosures, such as PCFs, EPDs, and PEFs, enable the use of bottom-up modeling with supplier-specific impact factors. These disclosures provide verified, product-specific environmental intensities (e.g., kg CO_2eq/kg), which can be directly applied to procurement quantities to yield high-resolution and defensible impact estimates (Pedersen and Remmen, 2022). This modeling approach is particularly effective for standardized, high-impact goods where such data are available and reliable.

When only organizational-level disclosures are available, such as corporate GHG inventories or revenue-based emissions intensities (e.g., kg CO_2eq/€), a top-down approach using supplier-specific monetary factors can be applied. This method involves multiplying financial expenditures by the supplier's reported emission intensity and offers a more precise alternative to generic sector-level proxies. While less granular than product-level modeling, it still reflects actual supplier performance and is especially useful for suppliers with diverse offerings or when product-level data is unavailable (Klaaßen and Stoll, 2021).

Finally, transactional or batch-level disclosures, such as shipment-specific carbon content, transport emissions, or renewable energy attributes, are best used to inform custom LCA modeling for high-impact or strategically significant products. These disclosures provide contextual specificity that can support tailored life cycle assessments, especially when standard databases fail to capture relevant production details (Meinrenken et al., 2020). Though more resource-intensive, custom modeling allows organizations to reflect real-world supply chain conditions in their Scope 3 impact assessments, especially for complex or high-impact procurement categories where environmental performance can vary significantly.

IV.4 Methods for Collecting Supplier Data

To enable the integration of supplier-specific environmental data into procurement-based environmental accounting models, organizations must adopt structured and scalable methods for data collection. These methods must account for variations in supplier capabilities, regulatory environments, and digital maturity. This section outlines three primary pathways for data collection:

IV.4.1 Direct Data Requests

Direct requests remain one of the most commonly used approaches for collecting supplier-specific environmental data, particularly in sectors where procurement relationships are strategic or contractual leverage is high.

Supplier Questionnaires

Custom or standardized questionnaires can be distributed to suppliers to solicit environmental disclosures related to products, operations, or supply chains (Stenzel and Waichman, 2023). These may include:

- Total GHG emissions (Scopes 1, 2, and 3),
- Product-level carbon footprints (in accordance with ISO 14067 or the GHG Protocol Product Standard),
- Environmental Product Declarations (EPDs) or underlying LCA documentation,
- Verification status of disclosed data (e.g., third-party certified vs. self-declared).

To increase response quality and reduce ambiguity, these questionnaires should be aligned with recognized disclosure frameworks such as the CDP Supply Chain Questionnaire, EcoVadis reporting modules, or sector-specific sustainability guidelines (e.g., EN 15804 in construction). The CDP Supply Chain Questionnaire is a globally recognized platform that enables companies to collect standardized climate-related disclosures from their suppliers, particularly focusing on GHG emissions, climate risks, and mitigation actions. EcoVadis, on the other hand, offers a widely used sustainability rating system that evaluates suppliers across environmental, social, and ethical dimensions based on documented evidence. Aligning with such frameworks enhances comparability, reduces reporting burden for suppliers already familiar with these systems, and facilitates integration into internal procurement and sustainability processes.

LCA-Based Reporting Templates

For suppliers with more advanced environmental capabilities, structured LCA-based reporting templates can be provided. These templates request quantitative disclosures on key impact categories (e.g., climate change, water use, land occupation) and methodological details such as system

boundaries, cut-off criteria, functional units, and geographic scope. Standardizing these templates helps ensure comparability across suppliers and simplifies integration into impact allocation models. This approach aligns with initiatives like the Partnership for Carbon Transparency (PACT), which promotes standardized, interoperable product-level emissions data exchange across global supply chains. When embedded into ERP systems, such templates can also facilitate automated data ingestion and real-time environmental reporting (Anaya and Qutaishat, 2022; WBCSD, 2023a).

To ensure data reliability, these templates should also include fields for specifying verification status, distinguishing between third-party certified results and self-declared values.

While direct data requests are effective in capturing detailed, supplier-specific information, their limitations include low response rates, especially among SMEs, and heterogeneity in data quality and methodological rigor. As such, direct requests are best applied selectively to high-impact or strategic suppliers, supported by training, incentives, or contractual clauses.

IV.4.2 Digital Integration

Digital integration methods aim to embed environmental data collection into existing procurement workflows, enabling more seamless, real-time, and scalable access to supplier-specific data.

APIs with Supplier Portals and E-Procurement Platforms

Enterprise Resource Planning (ERP) and e-procurement systems (e.g., SAP Ariba, Oracle Procurement Cloud, Ivalua) can be configured to collect environmental data through supplier portals (El Haouat et al., 2023). These portals may include:

- Mandatory sustainability fields during onboarding or bidding processes,
- Sections for uploading EPDs, PCFs, or GHG reports,
- Automated validation of file formats and metadata.

Through the use of Application Programming Interfaces (APIs), procurement platforms can retrieve or push environmental data between systems, allowing environmental intensities to be dynamically linked to product codes, suppliers, or transactions.

EPD Libraries and Digital Product Passports

In Europe, emerging policy tools such as the EU Digital Product Passport (DPP) initiative under the Ecodesign for Sustainable Products Regulation (ESPR) are expected to facilitate access to standardized product-level environmental information (European Commission, 2024). These digital passports will include embedded impact data (e.g., carbon intensity, recycled content, material composition) in

machine-readable formats and are expected to interface with procurement and inventory systems via open APIs (Lohar et al., 2023).

In the interim, procurement systems can already integrate with public or private EPD libraries, such as: ECO Platform (Europe-wide EPDs across sectors), INIES (France-specific EPDs for construction), EPD International (global platform for ISO 14025-compliant declarations). As presented in Chapter 2, these databases also support digital integration with procurement tools and life cycle assessment platforms.

Collaborative platforms such as Together for Sustainability (TfS) and Catena-X are also increasingly enabling supplier-specific, verified sustainability data to be exchanged across industries via interoperable digital infrastructures, accelerating Scope 3 data integration and standardization efforts.

Digital integration reduces the manual workload of sustainability teams and supports the automation of Scope 3 accounting, particularly for recurring purchases and standardized products (Uhlhorn et al., 2024).

IV.4.3 Data Trusts and Third-Party Intermediaries

In contexts where direct engagement or system integration is not feasible, such as fragmented supply chains, low-volume suppliers, or global sourcing, organizations may leverage third-party data providers or data-sharing intermediaries to access environmental data.

Third-Party Platforms and Data Providers

Several specialized platforms aggregate supplier-specific environmental data and provide scorecards, benchmarking, and verified disclosures. Key examples include:

- CDP Supply Chain: Enables buyers to access Scope 1–3 data and climate governance indicators disclosed by suppliers (CDP Supply Chain, n.d.).
- EcoVadis: Offers sustainability performance ratings based on self-reported and verified data across ESG themes (EcoVadis, n.d.).
- Climatiq: Provides emissions factors and supplier-level carbon data via API access, enabling integration into procurement or accounting tools (Climatiq, n.d.).

These platforms can improve data coverage across the supplier base, particularly for SMEs or international vendors that may lack in-house LCA expertise.

Blockchain-Based Systems and Data Trusts

Emerging technologies such as blockchain and distributed data trusts offer potential for secure, traceable, and tamper-resistant environmental data exchange. These systems allow suppliers to publish verified environmental attributes (e.g., product carbon content, renewable electricity use,

transport emissions) linked to specific batches, invoices, or supply chain nodes. While still nascent, such technologies are being piloted in sectors like food, and fashion (Varma et al., 2024; Vladucu et al., 2024).

Data intermediaries address scalability and coverage challenges but require careful validation. Buyers should assess the methodological transparency, temporal relevance, geographic alignment, and verification status of third-party data sources before integrating them into environmental accounting workflows.

IV.5 Supplier Engagement Strategies

Effective supplier engagement is critical to increasing the availability, quality, and integration of supplier-specific environmental data. Since suppliers differ in strategic relevance, environmental impact, and data maturity, engagement strategies must be tailored accordingly. A foundational step involves the prioritization of suppliers using a structured matrix that considers procurement volume, environmental impact potential, and existing data availability. This allows organizations to distinguish between strategic suppliers, who represent high environmental leverage or recurring spend, and transactional suppliers with limited influence or one-off purchases (Busse et al., 2016). Focusing efforts on high-priority suppliers enhances resource efficiency and improves the likelihood of meaningful data returns, and opens opportunities for joint innovation in supply chain sustainability efforts (Diebel et al., 2024).

Once priority suppliers are identified, organizations can deploy a combination of engagement approaches. Informational strategies include awareness campaigns, training materials, and knowledge sharing to educate suppliers on environmental disclosure frameworks, standards, and reporting expectations (Sancha Fernández et al., 2016). Collaborative engagement goes further, involving co-development of data, life cycle assessments, or joint sustainability initiatives . Contractual mechanisms may also be applied, incorporating environmental reporting requirements or data sharing obligations into procurement terms, tenders, and framework agreements (Stenzel and Waichman, 2023). In parallel, incentive-based mechanisms, such as preferred supplier status, scoring in supplier evaluation systems, or visibility in sustainability reports, can reward proactive suppliers and motivate broader adoption.

Finally, sustained supplier engagement depends on capacity building, especially among SMEs or suppliers with limited LCA expertise. Organizations can support suppliers through technical assistance, provision of standardized reporting templates, and access to LCA or EPD development tools. Establishing regional hubs, peer-learning platforms, or industry-specific training networks can further accelerate supplier readiness and reduce onboarding friction (Akella et al., 2024). These strategies help

to institutionalize environmental reporting and embed it within supplier routines, rather than treating it as a one-time compliance exercise.

IV.6 Data Quality and Verification

As supplier-specific data becomes more integrated into environmental accounting models, ensuring its credibility and comparability becomes paramount. Robust data quality and verification mechanisms are needed to mitigate the risks of misreporting, inconsistency, and greenwashing. To this end, organizations should establish clear acceptance criteria for supplier data, structured around international standards and methodological rigor (Lu, 2024).

Accepted disclosures should, where possible, conform to recognized ISO standards, such as ISO 14040 and ISO 14044 (for LCA), ISO 14067 (for carbon footprinting), and EN 15804 (for EPDs in the construction sector). These frameworks provide standardized guidance on system boundaries, functional units, allocation rules, and impact categories, ensuring consistency across suppliers and products (Gunaratne, 2025).

In addition to methodological compliance, verification status plays a critical role. Third-party verified data, such as certified EPDs or externally audited GHG inventories, should be prioritized over self-declared figures, particularly for use in public reporting, regulatory disclosures, or carbon pricing schemes. Where third-party verification is not feasible, organizations may choose to apply internal review processes, including plausibility checks, sensitivity analyses, or supplier interviews (Loreti et al., 2001; Oliveira et al., 2022).

Data should also be assessed for granularity and specificity. Site-level, product-specific disclosures with clear system boundaries and traceable data sources are preferable to generalized or global averages (Salemdeeb et al., 2017). A scoring framework can support this process, evaluating each data submission based on completeness, transparency, documentation quality, geographic and temporal relevance, and alignment with recognized standards. Integrating such a framework into procurement workflows ensures that only reliable data are accepted into impact models, while lower-quality inputs are either flagged for further review or substituted with conservative proxies.

IV.7 Roadmap for Supplier Data Integration

Moving from proxy-based environmental modeling to supplier-specific accounting requires a phased, strategically aligned roadmap. This progression should be grounded in both organizational capacity and supplier readiness, balancing ambition with feasibility. A maturity model can help frame this evolution, ranging from basic reliance on sectoral averages, to partial integration of supplier data, and ultimately toward widespread use of primary, product-specific disclosures across the supply chain.

In the short term, organizations can focus on high-impact, high-volume suppliers, typically the top 10–20 vendors by environmental spend or strategic importance. This may involve piloting data collection initiatives, embedding environmental criteria into tenders, and onboarding suppliers onto digital reporting platforms. Key procurement categories with well-defined products (e.g., construction materials, energy, IT equipment) serve as effective test cases for early implementation.

In the medium term, attention should shift to embedding data integration into core procurement processes. This includes updating ERP or e-procurement systems to store and link supplier environmental data, automating data validation workflows, and incorporating environmental performance into sourcing and contract management decisions. During this phase, supplier engagement should be broadened and supported by training, contractual mechanisms, and data-sharing incentives (Anaya and Qutaishat, 2022; El Haouat et al., 2023).

In the long term, supplier-specific environmental data should become an integral component of procurement governance and sustainability reporting. This requires investment in digital infrastructure, participation in regulatory data ecosystems (e.g., digital product passports), and alignment with evolving regulations such as CSRD (Köck et al., 2023; Stephan et al., 2019). By building these capabilities over time, organizations can transition from fragmented, reactive data collection to a robust, scalable, and decision-ready system for Scope 3 environmental impact accounting.

V. Hybrid Modeling and Decision Tree for Impact Allocation

This section contributes to an article by Essouid et al., "A Systematic Hybrid Approach to Scope 3 Procurement Emissions: Supporting Innovation and Decision-Making", which is currently under finalization.

Bottom-up accounting offers improved precision but is constrained by fragmented data and uneven supplier participation. To address these challenges, a hybrid modeling framework dynamically combines bottom-up and top-down methods based on data availability, product relevance, and modeling feasibility. A structured decision tree routes each procurement item through the most suitable pathway, ensuring both scalability and methodological rigor.

The hybrid modeling logic introduced in this thesis builds upon and advances the existing landscape of hybrid environmental accounting methods by operationalizing a Systematic Tiered Hybrid Life Cycle Assessment (STHL) framework specifically tailored to procurement-based Scope 3 emissions. While earlier studies such as Keil (2023), Finogenova et al. (2019), Cimprich and Young (2023), valuable contributions in developing Hybrid Life Cycle Assessment models, they remain constrained by key structural and operational limitations. Most notably, these models were not designed to function at the granular level of procurement line items, nor were they constructed to incorporate supplier-

specific disclosures or real-time transaction data from enterprise systems. Their assessments typically rely on aggregated expenditure categories, generalized emission intensities, or extrapolated averages, without direct engagement with suppliers or integration of product-level characteristics such as material composition, quantity, or geographic origin.

In contrast, the model developed in this thesis introduces a six-tier decision tree that dynamically routes each procurement item through the most appropriate modeling pathway based on actual data availability and relevance, including whether supplier-specific PCFs, EPDs, or physical quantity data are available. The framework is designed to interface directly with procurement and ERP systems, allowing the use of structured transaction-level metadata such as CPF codes, units, or supplier identifiers (e.g., SIREN). This enables organizations to model emissions with greater specificity and traceability, not only at the sector or supplier level but at the level of individual purchases.

Moreover, unlike prior models that treat supplier participation as static or optional, the STHL framework explicitly supports a progressive refinement logic: as suppliers improve data quality (e.g., reporting Scope 1+2+3 emissions or product-level disclosures), procurement items can move from coarse, sector-average modeling toward more precise, bottom-up accounting. This capacity to evolve over time, while maintaining consistency in methodology, positions this STHL model as a scalable and operationally implementable architecture for organizational Scope 3 accounting. In doing so, it fills a critical gap in the literature, by enabling companies to move beyond theoretical modeling and towards decision-ready, supplier-engaged carbon accounting workflows that are actionable at both the product and organizational levels. Furthermore, this framework fosters a new form of collaborative innovation, where buyers and suppliers co-develop more accurate data, better product designs, and targeted decarbonization strategies, positioning procurement not just as a site of data collection, but as a strategic arena for climate-driven transformation. This decision logic considers:

- Whether physical quantity data is available (e.g., kg, m^3, item count),
- Whether the product matches a representative LCI process,
- Availability of supplier-specific impact data (e.g., PCFs, EPDs, Scope 1+2+3 disclosures),
- Potential for automation or integration (e.g., structured metadata, classification codes),
- And, when required, feasibility of custom LCA modeling.

Based on these factors, each item is allocated to one of the following six modeling tiers:

- **Bottom-Up with Supplier-Specific Impact Factors**: Uses supplier-provided product-level emissions data, such as Product Carbon Footprints (PCFs) compliant with ISO 14067, Environmental Product Declarations (EPDs) conforming to EN 15804, or other LCA-based disclosures. Verified data is preferred (e.g., third-party reviewed, audit-backed, or program-

registered), but well-documented LCA results from the supplier may be accepted where verification is not yet available. This method offers the highest specificity and is most effective when suppliers operate in regulated sectors or have mature reporting systems.

- **Bottom-Up with Representative LCI Process Impact Factors**: Applied when physical quantities are available and matched to standard LCI processes (e.g., ecoinvent, Agribalyse) or peer-reviewed studies (Model III).
- **Top-Down with Supplier-Level Monetary Intensity Factors**: Used when a supplier reports total organizational GHG emissions and annual revenue. An emission intensity factor (e.g., kg CO_2eq/€) is calculated by dividing total emissions by turnover, then applied to procurement spend. This approach follows the GHG Protocol's "supplier-specific method" and provides more specificity than sector averages, especially when product-level data is not available (Paepe et al., 2023).
- **Top-Down with Product-Level Monetary Intensity Factors**: Used when only monetary data and classification codes (e.g., CPF Level 4) are available. Emissions are estimated using EEIO product-group intensities (Model II).
- **Top-Down with Sector-Level Monetary Intensity Factors**: A fallback when all other data is missing. Uses average sector-level intensities (Model I).
- **Custom LCA Study for High-Impact Items**: When a product is environmentally material and physical or supplier data exist but no suitable impact factor is available, a dedicated LCA study may be commissioned. Unlike the first option, where the supplier is responsible for the LCA modelling using their own primary data, this approach is used when the supplier provides partial data (e.g., energy use, materials) but does not disclose full process details. In such cases, the reporting company, if it has the necessary internal expertise, may calculate approximate emission factors using the supplied data and reasonable assumptions. While this method is more resource- and time-intensive, it is typically applied to hotspot categories where standard databases fail to capture key context-specific impacts (e.g., energy source, transport, material blend). The criteria for identifying high- or low-impact products can also be evaluated when a representative LCI process is available, to assess whether conducting a full LCA would yield more accurate and context-specific results.

This six-tiered approach supports progressive refinement: as suppliers improve data quality and systems mature, more items can "move up" the hierarchy, from proxy-based to physical or primary data models. It also supports strategic targeting, focusing LCA resources where they will provide the greatest decision-making value. A structured decision tree routes each procurement item through the most suitable modeling pathway, balancing accuracy and feasibility (Figure 4-8).

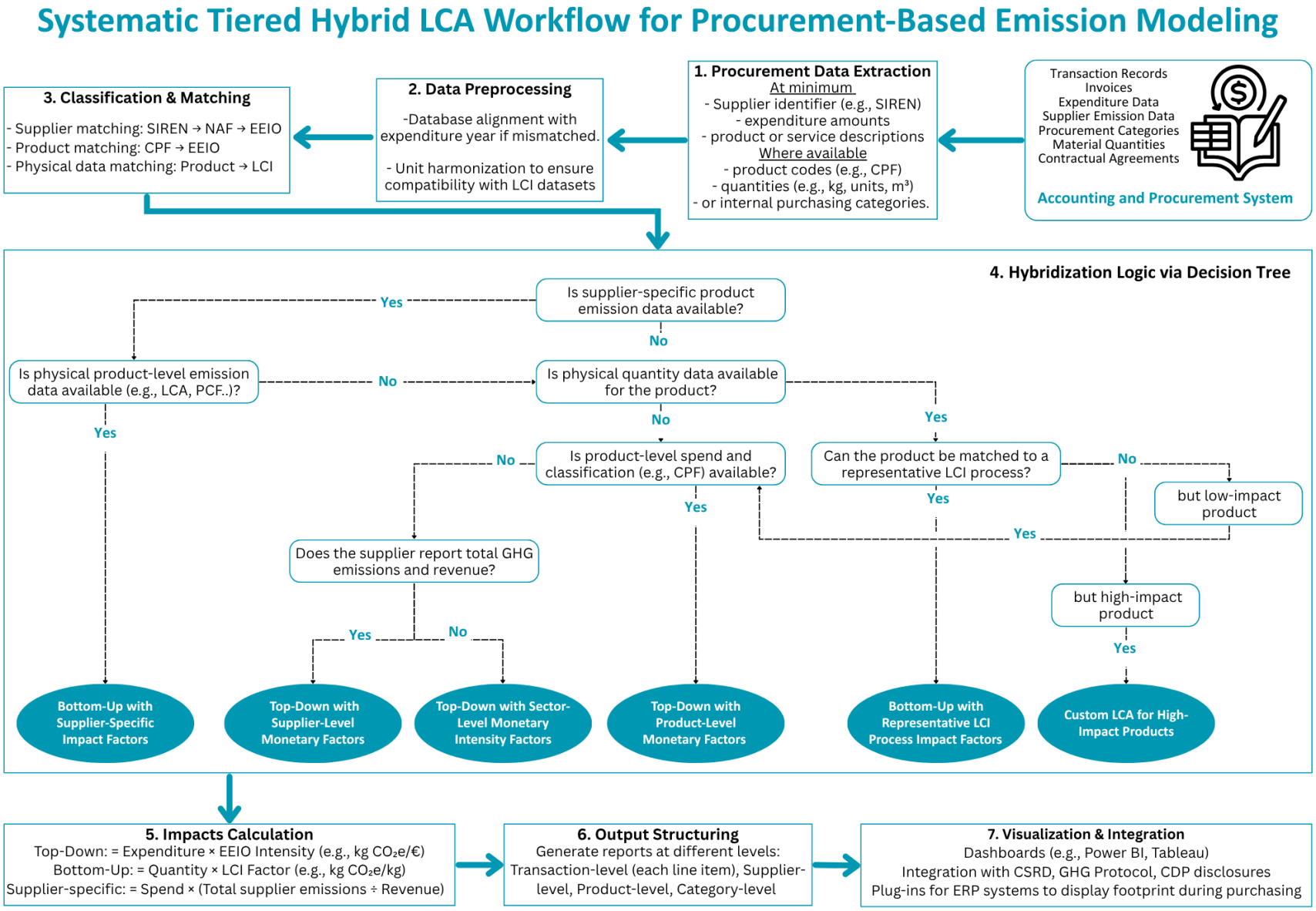


Figure 4-8 Systematic Tiered Hybrid LCA Workflow – Step-by-Step

This diagram illustrates the workflow for a Systematic Tiered Hybrid Life Cycle Assessment (STHL) applied to procurement data. It combines bottom-up and top-down modeling approaches based on the availability and quality of supplier, product, and transaction-level information. The model is applied in the French context, using national classification systems to ensure alignment with local procurement and environmental reporting structures. To operationalize this process, the following steps are undertaken:

Procurement Data Extraction : The implementation begins with extracting procurement data from the organization's ERP or accounting systems, such as SAP, Oracle, or Microsoft Dynamics. This data should include at minimum the supplier identifier (such as the SIREN code in France), expenditure amounts, product or service descriptions, and, where available, product codes (like CPF), quantities (e.g., kg, units, m^3), or internal purchasing categories. This data forms the foundation for assigning environmental intensities and calculating impacts.

Data Preprocessing : Following procurement data extraction, a key preprocessing step involves verifying the alignment between the year of financial expenditures and the year of the environmental intensity database (e.g., EXIOBASE). If both are from the same year, no inflation adjustment is needed. However, if the environmental database reflects a different base year than the procurement data (e.g., expenditures from 2024 but intensities from 2022), the environmental intensity dataset must be updated or adjusted accordingly. This ensures consistency in emissions estimation. No general inflation correction is applied to the monetary data itself; instead, the focus is on aligning or updating the environmental coefficients to reflect the actual year of expenditure.

This approach avoids misrepresenting environmental impacts due to temporal mismatches in underlying data. Physical quantities should be converted to standard units to match LCI factors (e.g., kg for materials, kWh for energy). Product and supplier descriptions may also need translation or normalization to facilitate semantic classification in later stages.

Classification and Mapping : In this step, procurement items are classified based on either their supplier's economic activity (top-down) or the product type (bottom-up). For supplier-level classification, the SIREN code is matched to a NAF code, which is then semantically mapped to an EXIOBASE sector using machine translation and embedding-based similarity matching. Alternatively, when CPF product codes are available, these are translated and semantically aligned with EXIOBASE product categories, enabling product-level environmental accounting. In cases where physical quantity data is provided, the products are manually matched to representative processes in databases like ecoinvent or Agribalyse based on their specifications and intended use. While EXIOBASE is widely used in Europe due to its alignment with EU sectoral classifications, other MRIO models are more suitable

in different regions; for example, the U.S. Environmental Protection Agency's USEEIO model is tailored for the U.S. context (US EPA, 2020), and Open IO, developed by CIRAIG, provides a Canadian MRIO framework (Maxime Agez, 2024). Selecting the appropriate model ensures geographical relevance and improves the accuracy of environmental impact estimations.

Hybridization Logic via Decision Tree : Each procurement record is evaluated through a structured decision tree to determine the most suitable modeling approach based on data availability and quality. The highest level of precision is achieved through bottom-up modeling using supplier-specific data such as EPDs or PCFs. If such data is unavailable, bottom-up modeling can still be applied using representative LCI processes and physical quantities. If physical data is lacking, the model defaults to top-down monetary modeling, using either product-level (CPF-based) or sector-level (NAF-based) EEIO intensities. In some cases, supplier-specific emissions intensities (e.g., emissions per euro of revenue) may be used. For high-impact or novel products with no existing data, a custom LCA study may be conducted as a last resort.

Environmental Impact Calculation : Once the appropriate modeling tier is selected, the environmental impact of each procurement item is calculated. For bottom-up approaches, the quantity of goods is multiplied by the relevant LCI-based impact factor (e.g., kg CO_2eq per kg). For top-down monetary methods, financial expenditures are multiplied by the applicable EEIO intensity factor (e.g., kg CO_2eq per €). When supplier-specific intensity data is available, it is used to estimate impacts more accurately than sectoral averages. This process is repeated across all procurement records, covering multiple impact categories such as carbon footprint and water scarcity.

Output Structuring and Reporting : After calculations are complete, the results are structured into various output formats for interpretation and reporting. These include transaction-level results (per purchase), supplier-level summaries, and aggregated results by category, sector, or product type. Data can be exported in CSV, Excel, depending on the organization's needs. These results are suitable for integration into internal dashboards, compliance reports (e.g., for CSRD or GHG Protocol), and supply chain sustainability initiatives.

Visualization and Integration : To support strategic decision-making and real-time insights, the model can be integrated into business intelligence tools such as Power BI. Custom dashboards can be built to visualize environmental hotspots, supplier impacts, or category-level footprints. Furthermore, the model architecture allows for potential integration with procurement systems, enabling dynamic environmental feedback during purchasing workflows, an essential feature for operationalizing sustainable procurement strategies.

B. Operationalizing the Hybrid Framework: Applications in Industrial Contexts

Building upon the conceptual foundation outlined in Section A, this section details the operational implementation of the hybrid environmental accounting model in real-world procurement contexts. It translates the systematic tiered methodology into a practical workflow applied to organizational procurement datasets, with a specific focus on the French construction and infrastructure sector.

The section outlines how the framework was implemented within Eiffage's procurement system, focusing on supplier engagement, data integration, and methodological refinement to support more accurate and actionable emissions calculation and tracking.

I. Eiffage's Organizational Structure and Emissions Estimation Pathways

Eiffage is one of the leading European construction and infrastructure groups, with over 84000 employees and more than 100000 projects delivered per year. In 2024, the Group generated €23.4 billion in revenue, with a strong international presence and a firm commitment to sustainable development. Eiffage operates across a wide spectrum of activities, from buildings and civil engineering to energy systems, real estate, and major infrastructure concessions. Its strategic position as a vertically integrated player, capable of delivering turnkey solutions from design to operation, gives it both scale and influence in shaping low-carbon transition practices across the construction value chain (Eiffage, 2024).

In line with its climate commitments, Eiffage has adopted a 1.5°C science-based trajectory validated by the SBTi, which dictates a 46% reduction in Scope 1 and 2 emissions and a 30% reduction in Scope 3 emissions (upstream and downstream) by 2030, using 2019 as a baseline. The group's emissions reduction strategy is embedded in a broader low-carbon roadmap that includes life-cycle impact analysis, supplier engagement, circular economy practices, and the decarbonization of materials.

Eiffage's organizational structure is illustrated in Figure 4-9, which provides a simplified overview of its operational hierarchy. The Group is structured into four main divisions, Infrastructure, Construction, Concessions, and Energy Systems, each operating under a decentralized management model. These divisions (or branches in French, "BR") are subdivided into Regional Directorates (or Directions Régionales in French, "DR") based on geographical areas (e.g., Île-de-France, Occitanie), and further segmented into Business Units (BU). BUs serve as the operational cores responsible for project execution, procurement, subcontractor management, and the on-site application of environmental procedures, such as material tracking and waste management.

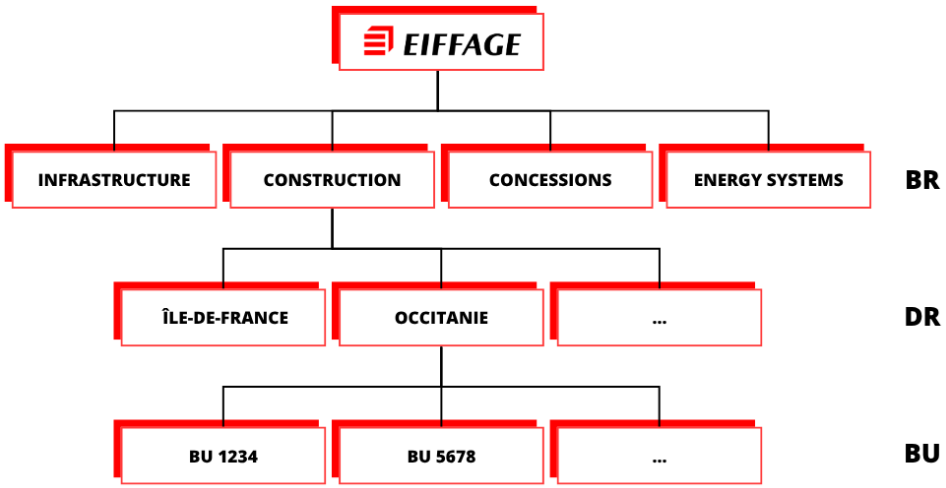


Figure 4-9 Simplified Organizational Structure of Eiffage Group

This decentralized structure supports agility and local responsiveness but also introduces complexity in harmonizing Scope 3 emissions reporting and integrating supplier-level environmental data across multiple entities. Addressing this challenge requires a transition from general estimations to more precise measurement-based accounting practices.

This need for methodological refinement is captured in Figure 4-10, which illustrates the current reliance on monetary emission factors (±50% uncertainty) and outlines the path toward more accurate approaches, including supplier-specific data (±20%) and product-level life cycle assessments (±5%). The figure highlights the Group's strategic objective: to progressively move upward along this data quality hierarchy, shifting from estimation-based methods toward physically measured emissions grounded in verified LCA data. This trajectory supports Eiffage's ambition to embed carbon transparency and accountability into its procurement and operational decisions.

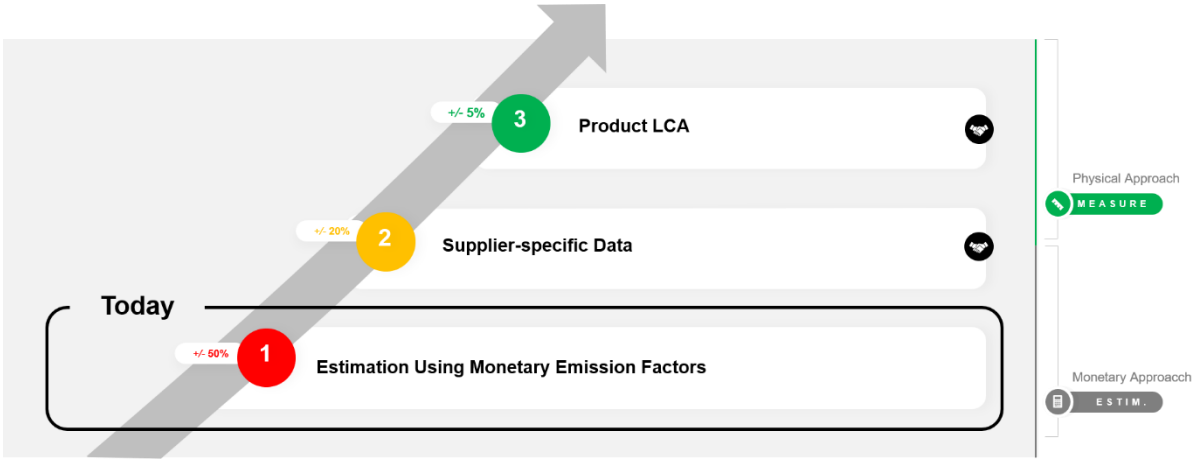


Figure 4-10 Transition Pathway from Monetary Estimations to Product-Level Carbon Measurement (adapted from CNA (2024) and Eiffage's internal documentation)

II. LODACE: Eiffage's Sustainable Digital Procurement Platform

The implementation of the hybrid environmental accounting framework within Eiffage is supported by a robust digital procurement ecosystem, at the core of which lies the LODACE sourcing platform. As part of Eiffage's broader digital transformation strategy, LODACE serves as a central component of the company's Procurement Information System, which professionalizes and secures procurement practices through shared processes and standardized tools.

LODACE sourcing fulfills several strategic functions in the procurement life cycle:

- Supplier and subcontractor management, including database maintenance and risk evaluation.
- Contract life cycle management, from drafting to electronic signature.
- Digitalized procurement procedures, such as e-sourcing and tender management.
- Spend analysis and oversight, which enables cost control and transparency.

Critically for this thesis, LODACE also integrates carbon reporting functionalities, enabling procurement teams to identify the most CO_2-intensive purchasing categories based on spending volumes and operational activities. This feature aligns directly with the aims of hybrid Scope 3 accounting by providing actionable insights at the intersection of financial expenditure and environmental impact.

In addition to its strategic functions, the LODACE platform features a dedicated "Reporting Carbone" interface (Figure 4-11), which enables procurement teams to filter and analyze carbon-related data across multiple dimensions. Users can select by date, geographic zone, branch, region, company, and establishment, offering fine-grained control over carbon reporting. Advanced filtering options include carbon criticality, internal/external supplier status, and the ability to exclude specific procurement categories such as subcontracting or real estate. The tool also allows identification of parent and child panels and provides a field for specifying a child supplier panel, further enhancing traceability. These features empower users to navigate carbon data at both strategic and operational levels, aligning procurement decisions with Eiffage's sustainability objectives and reinforcing the utility of LODACE in Scope 3 accounting.



Figure 4-11 Carbon Reporting Interface Within LODACE Platform, Allowing for Multi-Criteria Filtering and Visualization of Carbon Related Procurement Data.

LODACE is also supported by a suite of complementary digital tools that reinforce the environmental dimension of procurement:

- Ecosource: a multi-criteria product comparison tool that evaluates environmental performance across similar use products, allowing buyers to make more sustainable selections;
- BlueOn: an environmental data marketplace listing products with verified Environmental Product Declarations (EPDs), based on Life Cycle Assessment (LCA) methodologies (BlueOn, n.d.).

Together, these systems form a digitally enabled ecosystem for sustainable procurement, embedding environmental insights directly into sourcing workflows. For the research project, this ecosystem provides an ideal testing ground for implementing and refining the hybrid framework, as it allows for the integration of monetary and emissions data into procurement analytics. By leveraging these tools, Eiffage advances toward a procurement model that is not only economically efficient but also environmentally accountable, demonstrating the practical feasibility of hybrid Scope 3 accounting in a large-scale industrial context.

III. Diagnostic of 2024 Procurement Expenditure and Scope 3 Attribution

This section presents an overview of Eiffage's 2024 procurement expenditure, with a focus on its alignment with Scope 3 categories under the GHG Protocol. By linking financial outlays to associated emissions, the analysis identifies high-impact procurement areas—particularly within materials—where decarbonization efforts can be most effective. Special attention is given to ready-mix concrete, due to its disproportionate contribution to overall emissions.

IV.1 Expenditure Mapping and Scope 3 Categorization of Operational Purchases

Figure 4-12 presents the distribution of organizational expenditure across operational categories for the year 2024, with visual encoding to distinguish Scope 3 attribution under the GHG Protocol. Categories marked with diagonal hatching (///) correspond to Scope 3 – Category 1: Purchased Goods and Services, while dotted patterns (...) indicate Scope 3 – Category 2: Capital Goods. According to the GHG Protocol, Capital goods are final products that have an extended life and are used by the company to manufacture a product; provide a service; or sell, store, and deliver merchandise (WRI and WBCSD, 2013). In financial accounting, capital goods are treated as fixed assets or as plant, property, and equipment. Examples of capital goods include equipment, machinery, buildings, facilities, and vehicles.

While EL – Subcontracting dominates the expenditure profile (32.4%), it presents considerable barriers for carbon quantification due to fragmented supply chains and the lack of granular emissions data. Subcontractors vary widely in their scope, some provide only labour, while others include materials,

making the category even more dispersed and inconsistent. Given these complexities, it is not currently a priority for detailed carbon analysis.

Importantly, the category HL – Materials exhibits a disproportionately high climate impact: although it accounts for only 7.5% of financial outlay, it contributes a striking 32.4% of GHG emissions. This discrepancy underscores the carbon intensity of construction materials, which are directly embedded in physical assets like infrastructure and buildings. Prioritizing HL within Scope 3.1 monitoring thus enables more precise tracking of embodied emissions and informs upstream decarbonization strategies during design and procurement phases.

Conversely, categories like FL – Supplies and IL – Machinery show a more balanced alignment between expenditure and emissions shares. Capital goods, typically represented under Scope 3.2, remain relevant due to their life cycle impact, but their emissions are harder to address within short-term procurement cycles given accounting conventions and delayed amortization of environmental impacts.

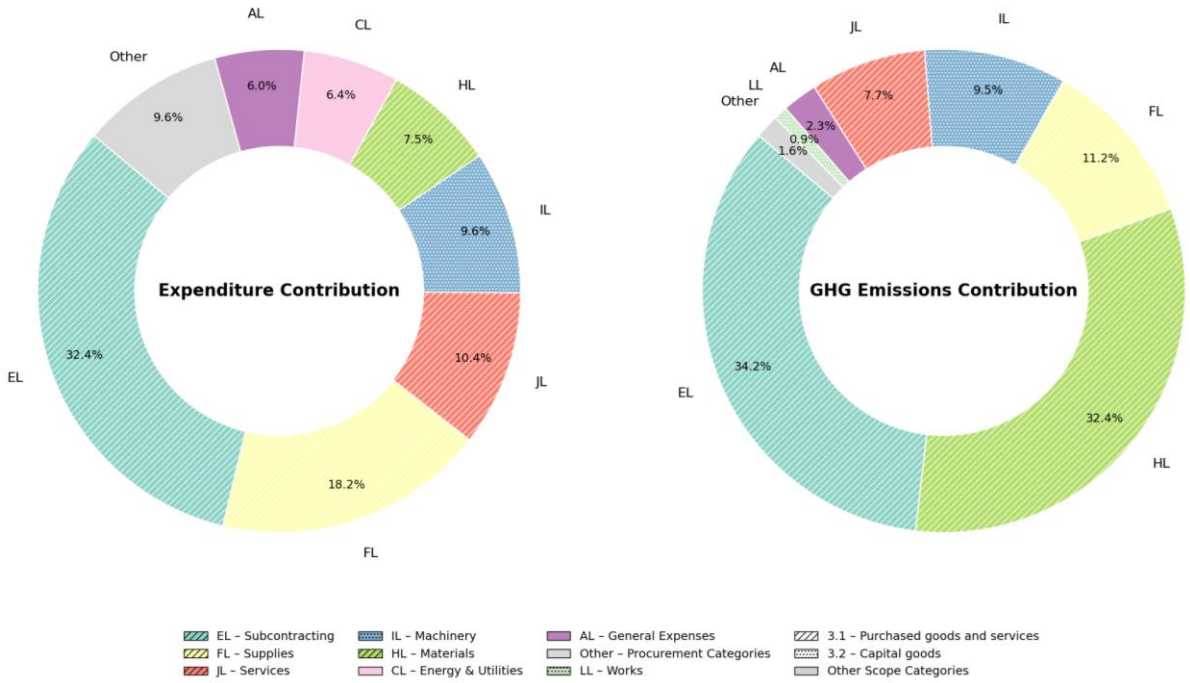


Figure 4-12 Distribution of 2024 Expenditure and GHG Emissions by Procurement Category and Scope 3 Attribution

IV.2 Quantitative Evaluation of Material Categories for Decarbonization Prioritization

The environmental and financial significance of material procurement within Eiffage's construction operations is illustrated in Figure 4-13, which presents a dual donut chart visualization of the relative contributions of key material categories to GHG emissions and procurement expenditure.

This analysis is based on Eiffage's internal reporting data for the year 2024, using the emission factors

currently applied in the company's carbon accounting system, which reflect standardized intensities for each material category.

The data reveal that concrete-related materials, in particular ready-mix concrete (HL0501) and precast concrete (HL1000), constitute the most impactful procurement categories. Ready-mix concrete alone accounts for 29.9% of total emissions and 23.2% of expenditure, while precast concrete contributes an additional 9.3% of emissions and 11.0% of costs. Together, these two subcategories dominate the HL panel, previously identified as the highest-emitting procurement category in Eiffage's broader expenditure-emissions mapping. Collectively, these concrete products are responsible for nearly 40% of total GHG emissions from material purchases, and over 34% of its financial outlays, underscoring their centrality in both the environmental and economic profiles of the company's supply chain.

In contrast, steel products, structural steel (HL0000) and reinforcement CF/CFA (HL0002), represent a more modest share of material-related impacts. Together, they contribute approximately 8.2% of expenditure, yet do not appear among the dominant sources of emissions in the GHG chart, suggesting a relatively lower carbon intensity per euro spent compared to concrete. Bitumen and derivatives (HL2501) are also significant, contributing 13.7% of expenditure and 15.8% of emissions, and may warrant further investigation.

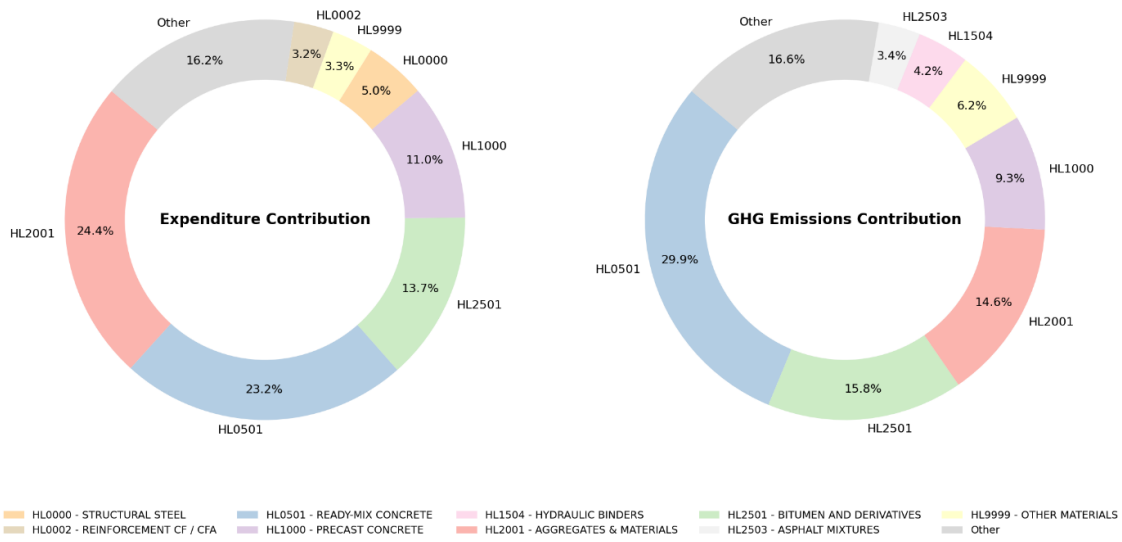


Figure 4-13 Relative Contribution of Purchased Material Categories to 2024 GHG Emissions and Expenditure at Eiffage

These results further validate the high-carbon nature of the HL material category identified in the previous section, and reinforce the importance of disaggregating it into material-specific components for effective mitigation. The sharp contrast between concrete and other material types, such as steel, highlights the need for tailored strategies that reflect actual emission drivers rather than spending volumes alone.

This prioritization is also supported by the carbon criticality assessment provided by the LODACE sourcing platform (Figure 4-14), which visualizes GHG risk levels across material families regardless of their financial weight. A carbon criticality assessment is a diagnostic tool that ranks materials or activities based on their relative greenhouse gas (GHG) emission intensity and strategic importance, helping prioritize decarbonization efforts. In this representation, ready-mix concrete (HL0501) appears in deep red (indicating a critical risk level) while many other materials fall into orange, yellow, or green zones. The color-coded criticality scale (red = critical, orange = important, yellow = medium, green = low) further emphasizes the urgency of targeting high-emission materials like concrete for decarbonization.

Instead of relying on generic emission factors, the following sections will focus on the integration of supplier-specific emissions data for ready-mix concrete. By refining emission factors at the supplier level and injecting this differentiated information into carbon accounting workflows, the approach aims to enhance the granularity, accuracy, and decision-making value of Scope 3.1 calculations. This operationalizes the hybrid accounting framework introduced earlier, enabling Eiffage to align procurement activities with decarbonization targets in a more data-driven and supplier-engaged manner.

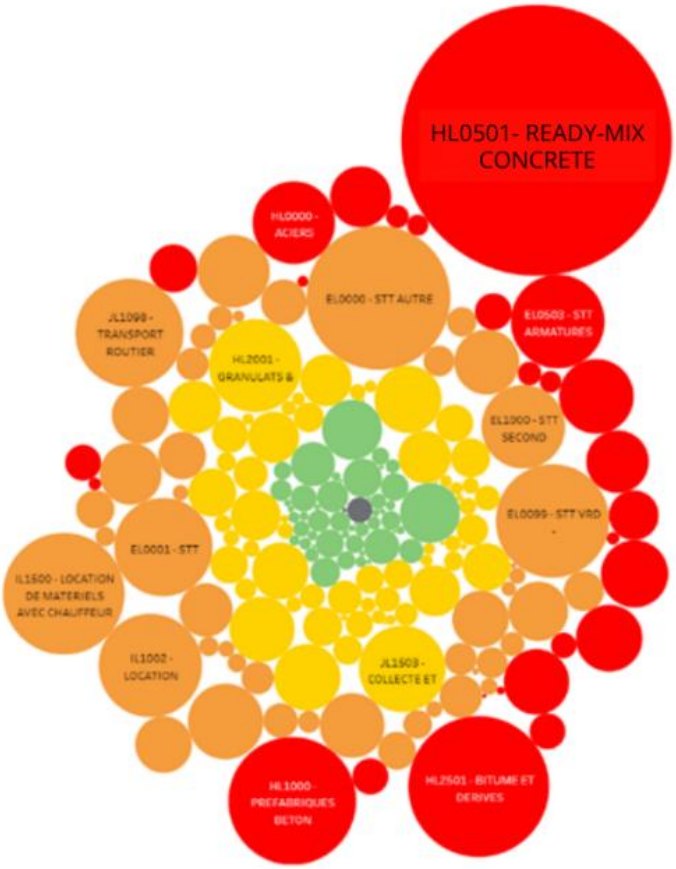


Figure 4-14 Carbon Risk Criticality of Material Families According to LODACE Platform (2024)

IV.3 Variability in Emission Factors Across Data Sources

Eiffage's GHG emissions accounting tool employs a distinctive methodological framework based on the development of estimated emission factors expressed in monetary terms ($kgCO_2e/€$). These estimates are derived through a combination of procurement insights, and aggregated emissions data from various sources. The resulting in-house monetary baseline is designed to integrate seamlessly with the company's cost structures, ensuring operational compatibility and facilitating comprehensive internal carbon reporting. Notably, this approach does not rely directly on external input-output (IO) models; rather, it represents a custom-built estimation framework tailored to Eiffage's specific procurement practices and market conditions. Acknowledging the limitations of purely monetary estimations, particularly their propensity to average emissions across heterogeneous products, Eiffage selectively refines certain material categories by incorporating high-resolution physical data. This refinement process involves substituting or adjusting the monetary emission factors with more precise values derived from physical datasets, which are converted to a monetary basis using Eiffage's internal pricing structure.

To evaluate the consistency, and variability of Eiffage's emission factors, a comparative analysis was conducted across six representative material categories: ready-mix concrete (HL0501), concrete blocks (HL1000), lime (HL1501), cement (HL1502), aggregates (HL2001), and bitumen (HL2501). Emission factors from five distinct sources were compiled and standardized to a common unit of $kgCO_2eq$ per EUR2024. These sources included Eiffage's internal emission factors, two physical life cycle inventory databases (ecoinvent v3.9.1 and Base Empreinte® - ADEME), and two external monetary IO databases (Exiobase 3.8 and CEDA 2024).

For ecoinvent, emission factors were derived using the bottom-up modeling approach presented in Section 4.A.III, which involves manually matching procured products to representative LCI processes based on physical characteristics (e.g., mass, volume, material type), retrieving impact factors per physical unit (e.g., kg CO_2e/kg), and converting these to monetary values using Eiffage's average 2024 unit prices. This method ensures that emission estimates are grounded in the actual material composition and production pathways of purchased goods, offering greater specificity than aggregated monetary models. For Exiobase, environmental intensities were calculated following the top-down monetary model detailed in Section 4.A.I, including semantic mapping, inflation normalization, and environmental characterization via the Impact World+ method. For physical databases, emission factors originally expressed per physical quantity (e.g., $kgCO_2e/T$) were converted to a monetary basis using Eiffage's 2024 baseline procurement prices, provided by internal purchasing experts. For monetary databases, values originally in €2022 (Exiobase) and $2022 (CEDA) were adjusted to €2024 using appropriate exchange rates and inflation indices to ensure unit comparability.

The compiled data was then visualized using a combination of boxplots and discrete markers in Figure 4-15. Ecoinvent, known for its high granularity and process specificity, was used as the reference benchmark and is represented by distributions (boxplots) showing the interquartile range, median, and outliers for each material category. Individual values from other datasets, including Base Empreinte® ADEME, Exiobase, CEDA, and Eiffage, were overlaid as individual points to enable direct visual comparison against the ecoinvent benchmark.

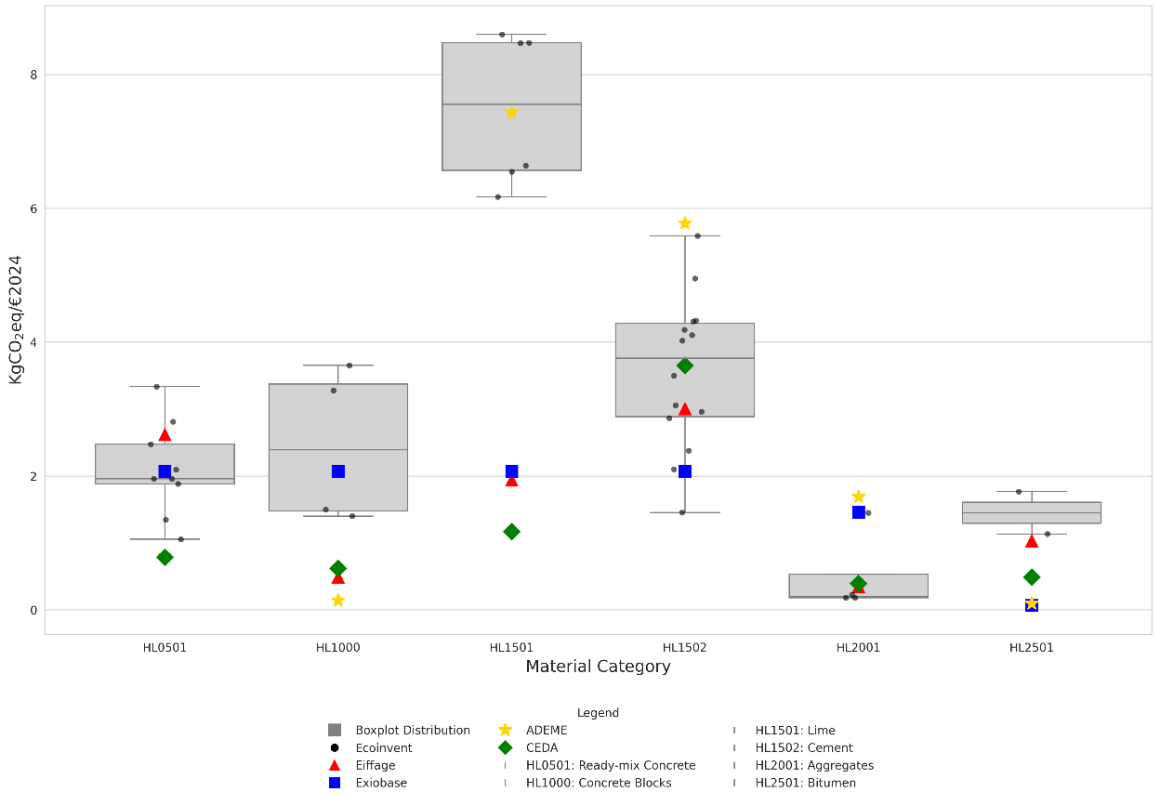


Figure 4-15 Comparison of Emission Factors by Material Category Across Multiple Data Sources (kg CO_2e/EUR2024)

This visualization highlights not only differences in central tendencies but also variation within and between databases, allowing for a diagnostic assessment of potential under- or overestimation patterns in Eiffage's current GHG accounting tool.

Figure 4-15 illustrates the relative positioning of Eiffage's estimated GHG emission factors (in kgCO_2e/EUR2024) compared to external reference datasets across six key construction material categories. The alignment between Eiffage and the ecoinvent benchmark is not strongest in the categories refined with physical data (i.e., ready-mix concrete – HL0501 and bitumen – HL2501).

In fact, the figure shows that:

- For ready-mix concrete (HL0501), although Eiffage has applied physical refinement, its emission factor lies just above the upper quartile of the ecoinvent distribution. While it is not an extreme outlier, the value is higher than the ecoinvent median and interquartile range,

suggesting a potential overestimation. This could result from a conservative emission factor, a lower internal price baseline, or misalignment between the physical dataset used and Eiffage's market context.

- For bitumen (HL2501), although Eiffage has refined this category using physical data, its emission factor is located near the lower whisker of the ecoinvent distribution and significantly below the interquartile range. This positioning suggests that the current value may underestimate emissions relative to process-based benchmarks. However, Eiffage's value still lies closer to ecoinvent than the monetary-based values from CEDA, Base Empreinte® ADEME, and Exiobase, which are all clustered near zero. The result raises questions about the refinement process, particularly whether the physical dataset used was representative of typical bitumen production, and whether the monetization step (via internal price conversion) introduced a downward bias.

By contrast, in categories that are not physically refined:

- For concrete blocks (HL1000), Eiffage's emission factor lies well below the ecoinvent distribution, falling outside the lower whisker. It is, however, aligned with the values reported by CEDA and Base Empreinte® ADEME, all of which are significantly lower than both the ecoinvent benchmark and the Exiobase estimate. This discrepancy suggests that Eiffage's monetary-based factor for this category may underestimate emissions, potentially due to price distortions, aggregation issues, or the absence of refinement with physical data. The position of Exiobase near the ecoinvent median indicates that a monetized approach can be closer to LCI references, but only when structured appropriately.
- For lime (HL1501), all monetary-based emission factors, including those from Eiffage, Exiobase, and CEDA, lie well below the ecoinvent distribution and fall outside the lower whisker. This consistent underestimation suggests that the sectoral aggregation and pricing structure underlying these estimates may not adequately capture the true carbon intensity of lime production, which is highly energy-intensive due to calcination. In contrast, Base Empreinte® ADEME's value aligns closely with the ecoinvent median, reinforcing the reliability of process-based physical data for this category.
- For cement (HL1502), although the Eiffage emission factor is derived from a monetary estimate, it falls comfortably within the interquartile range of the Ecoinvent distribution and shows close alignment with CEDA. This suggests that for cement — a well-documented, high-impact material — the monetary estimation approach performs relatively well, likely due to a strong signal in both emission intensity and pricing. Exiobase, while slightly lower, remains within the overall distribution. Base Empreinte® ADEME's value sits higher, above the

ecoinvent upper whisker, potentially reflecting methodological or system boundary differences.

- For aggregates (HL2001), the emission factors from Eiffage, CEDA, and Exiobase all cluster near the lower end of the ecoinvent range, but remain within or close to its distribution. However, they fall well below the Base Empreinte® ADEME value, which may include broader or more recent life cycle stages such as transportation. While not clearly underestimated relative to ecoinvent, the results suggest that monetary-based methods may not fully capture upstream variability, especially for bulk materials with low price signals and diffuse supply chains.

These observations suggest that physical refinement does not automatically guarantee better alignment unless the conversion process (monetary normalization, data selection, pricing) is robust and representative. Conversely, some purely monetary estimates in Eiffage's tool perform reasonably well, indicating that careful estimation and price alignment can yield acceptable results even without physical LCI data. However, it is important to note that these findings are based on a selected set of construction-related material categories, and their applicability may not generalize to other domains such as electronics, food, or textiles, where different supply chain dynamics, impact drivers, and data structures may influence model performance.

Overall, this analysis underscores the importance of systematic validation for both refined and non-refined emission factors. While Eiffage's model proves effective in certain cases, its accuracy depends heavily on the robustness of the conversion process, particularly for physically refined factors, where the methodological benefits only materialize if data selection, price normalization, and matching procedures are properly calibrated.

The comparative results also reveal a consistent pattern across databases: monetary IO sources such as Exiobase and CEDA tend to produce lower emission factors, reflecting their inherent limitations in capturing material-specific variability. This is especially problematic for high-impact categories like cement and aggregates, where sector-averaged values obscure meaningful process-level differences. In contrast, datasets like ecoinvent and Base Empreinte® ADEME offer higher central tendencies and wider distribution ranges, better reflecting the diversity of real-world production conditions.

These findings confirm that physically refining emission factors enhances alignment with detailed LCA benchmarks, particularly in construction-related materials. However, they also highlight persistent methodological gaps in non-refined categories, suggesting that further improvements, such as incorporating supplier-specific emissions or expanding the use of high-resolution LCI data, would substantially increase accuracy and decision relevance. That said, these insights are specific to the

construction materials analyzed and should not be generalized across all sectors, where supply chain complexity and data structures may differ significantly.

The implications of this modeling architecture are twofold. On one hand, Eiffage's monetary-based framework offers high operational compatibility, aligning seamlessly with procurement workflows and enabling internal carbon-cost coupling. On the other hand, continued reliance on unrefined monetary proxies introduces accounting risks, especially under tightening regulatory frameworks like the CSRD. Inaccurate estimates in high-volume categories could impair Eiffage's ability to credibly report and reduce Scope 3 emissions, and the lack of differentiation between suppliers limits the model's utility in driving low-carbon sourcing.

To strengthen methodological robustness, Eiffage should scale up the integration of supplier-specific physical data, particularly through EPDs or verified carbon footprints. Where such data is unavailable, correction factors from high-quality LCI datasets can be used to adjust monetary estimates. Ultimately, while the current approach is pragmatic and tailored to operational realities, its evolution toward a more supplier-informed and science-based model will be critical for ensuring transparency, compliance, and leadership in sustainable procurement.

IV. Data collection from suppliers

Reliable assessment of the environmental footprint of construction materials depends heavily on the availability and quality of upstream data. In the context of this study, particular attention was given to concrete, a material with high embodied carbon and widespread use across Eiffage projects. The data collection process aimed to gather detailed technical and volumetric information directly from concrete suppliers, focusing on ready-mix concrete delivered to various Eiffage entities. This section outlines the procedures followed to obtain this data, the challenges encountered in terms of technical consistency and terminology, and the methods used to harmonize heterogeneous inputs into a usable and analyzable format.

V.1 Data Collection Process for Concrete Volumes, Prices and Emissions

The retrieval of data related to concrete volumes at Eiffage followed a collaborative and iterative approach, combining internal organizational processes with the mobilization of professional networks within the construction materials sector. This effort was carried out jointly with the national purchasing lead for the concrete product family at Eiffage, whose expertise and long-standing relationships with suppliers were instrumental in accessing the required data.

Within Eiffage, purchasing managers typically handle supplier relations at a local level. However, in this case, coordination at the national level enabled a more centralized and effective strategy for engaging with major suppliers, particularly national key account managers of large concrete producers.

The data collection process relied heavily on direct engagement and well-established working relationships with supplier representatives. Drawing on this internal expertise and professional network, the national purchasing lead initiated contact with national-level sales managers at major suppliers. The objective was to obtain data on delivered volumes, corresponding concrete mix formulations, and, where available, associated CO_2 emissions.

Initial efforts focused on engaging national-level suppliers with a wide geographical footprint across France and significant commercial volume with Eiffage. For the year 2024, data was successfully collected from a group of suppliers accounting for 75% of Eiffage's total expenditure on ready-mix concrete, ensuring a representative coverage of the company's procurement activities. Requests for data were typically addressed to commercial contacts, who would either handle the request themselves or refer it to data specialists or internal analysts. In some cases, no direct contact with data personnel was established, and the exchanges remained within the commercial domain.

The nature and quality of the data obtained varied considerably across suppliers. Some were able to provide well-structured and comprehensive datasets. For instance, Eqiom submitted highly detailed and consolidated data, which, while requiring further processing, offered substantial analytical value. Other suppliers provided more crude exports, often in the form of pivot tables or aggregated summaries with limited utility, particularly when data granularity was too localized (e.g., only covering a specific site). In many instances, critical variables such as the concrete formulation or cement type were missing from the initial datasets.

In several cases, the retrieval of usable data required multiple rounds of correspondence. The process often extended over one to two years, depending on the responsiveness of commercial contacts, their capacity to extract relevant data internally, and the iterative clarification of the request's scope and structure. For example, in the case of Cemex, separate data on cement type and strength class was eventually obtained, although this level of detail was not consistently provided across all suppliers or reporting years.

The data request is typically reiterated annually, usually around December or January, to capture information from the preceding year. However, structural inconsistencies between yearly datasets can lead to loss of comparability and require additional harmonization efforts.

Once the datasets were received, a manual data processing phase was undertaken. This involved validating the internal consistency of reported volumes against recorded expenditures, identifying missing elements, and assessing the extent to which the data reflected actual procurement activities. A key objective of this phase was to establish a reliable order of magnitude for the volumes involved

and to enable a preliminary estimation of carbon emissions, based on aggregated consumption figures and average pricing differentiated by cement type.

Despite the challenges inherent in accessing and consolidating such technical and commercially sensitive information, the overall collaboration with suppliers proved constructive. Many suppliers demonstrated a clear willingness to engage with the process, providing data despite internal constraints related to extraction capacity, confidentiality, or system limitations. Their responsiveness and openness to dialogue greatly facilitated the iterative nature of the data collection effort. In several cases, the exchanges evolved over time into more structured and transparent communication channels, reflecting a shared interest in supporting initiatives aimed at improving environmental data tracking and procurement transparency.

V.2 Concrete Standard NF EN 206+A2/CN and BPS Designation

NF EN 206+A2/CN (Afnor, 2021) is the French national implementation of the European standard EN 206-1, developed by the Comité Européen de Normalisation (CEN). It includes a National Annex that adapts the standard to the French context, and has served as the normative reference for structural concrete since 2005 for both site-mix and ready-mix concrete used in buildings and civil engineering structures.

The standard defines the requirements for concrete constituents (cement, aggregates, admixtures, mixing water), sets performance-based criteria, and assigns responsibility among stakeholders including the specifier, producer, and user. Importantly, NF EN 206-1 places significant emphasis on concrete durability by integrating environmental exposure classifications alongside mechanical and workability requirements.

V.2.1 Definition and Role of BPS Concrete

Among the three categories of concrete defined by the standard, Concrete with Specified Properties (Béton à Propriétés Spécifiées, BPS), Concrete with Prescribed Composition (Béton à Composition Prescrite, BCP), and Concrete with Prescribed Composition within a Standard (Béton à Composition Prescrite dans une Norme, BCPN), BPS is the most prevalent in professional practice. A BPS concrete is characterized by performance specifications such as compressive strength, durability against environmental exposure, consistency (workability), and permissible chloride content. The specifier is responsible for defining these properties, while the producer assumes responsibility for selecting materials and mix design strategies that satisfy the given specifications (Afnor, 2021). This performance-based approach enables adaptability in concrete formulation, while simultaneously ensuring that the concrete will meet structural and durability requirements under specific service conditions.

V.2.2 Parameters Defining BPS Concrete

The designation of BPS concrete according to NF EN 206-1 is a standardized expression comprising a series of interdependent parameters (Afnor, 2021). Each of these parameters plays a critical role in defining the mechanical performance, durability, and workability of the concrete. The typical designation takes the form: **BPS NF EN 206-1 Cxx/yy [Exposure Class] Dmax zz Sx CL 0.aa** (see example in Figure 4-16)

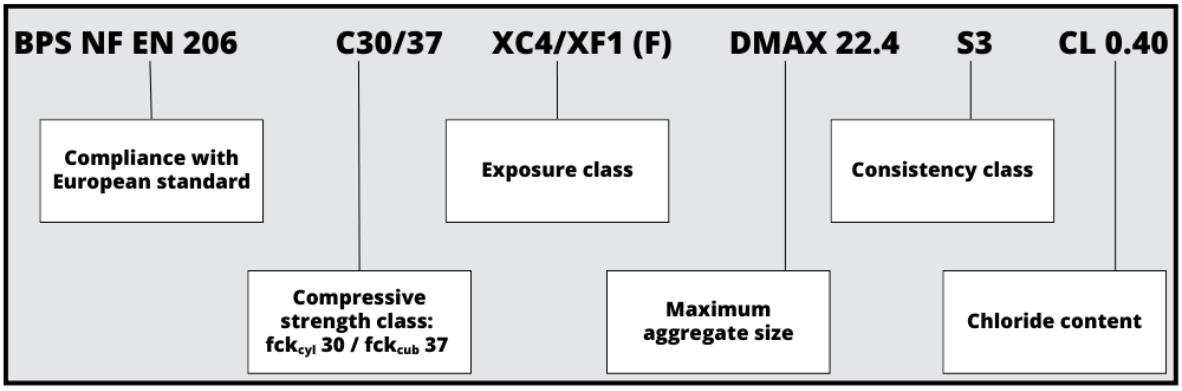


Figure 4-16 Designation of a Concrete (BPS) Compliant with the NF EN 206-1 Standard

A detailed discussion of each component is provided below.

❖ *Compressive Strength Class (Cxx/yy)*

The compressive strength class refers to the characteristic strength of concrete, measured at 28 days under standardized curing conditions. The notation includes two values:

- Cxx: compressive strength (in MPa) measured on cylindrical specimens (typically 150 mm × 300 mm),
- Cyy: compressive strength (in MPa) measured on cubic specimens (typically 150 mm × 150 mm × 150 mm).

This dual notation accounts for differences in test geometry and reflects the international variability in testing standards. The strength class directly informs the structural capacity and is therefore a fundamental parameter in both design and quality control.

❖ *Exposure Class*

Exposure classes describe the environmental conditions to which the concrete will be subjected during its service life. These classes are designed to ensure the long-term durability of the concrete and its embedded reinforcements. The NF EN 206-1 standard distinguishes five primary exposure mechanisms, each further subdivided into classes:

- XC (carbonation-induced corrosion): relevant for reinforced concrete exposed to air and moisture.
- XF (freeze–thaw action): accounts for freeze–thaw cycles, with or without de-icing agents.
- XS (chloride attack from sea water): applies to marine environments.
- XD (chloride attack from non-marine sources): typical of road structures exposed to de-icing salts.
- XA (chemical attack): includes aggressive soils and industrial effluents.

Each exposure class entails minimum requirements for cement content, water-to-cement ratio, air entrainment, and binder type. In French applications, exposure classes are denoted with an (F) suffix to account for local climatic and geographic adjustments.

❖ *Maximum Aggregate Size (Dmax)*

The maximum nominal aggregate size (Dmax) represents the largest particle size permitted in the concrete mix. It is selected based on several factors including:

- Reinforcement spacing and cover,
- Element thickness,
- Pumpability and workability requirements.

Larger aggregates reduce the cement paste volume needed, potentially lowering shrinkage and thermal effects, while smaller aggregates enhance surface finish and mix homogeneity.

❖ *Consistency Class (Sx)*

Consistency, or workability, is classified according to slump measured via the Abrams cone test. The five standard classes (S1 through S5) cover slump values from 10 mm (very stiff) to over 220 mm (self-compacting). Workability must be appropriate for the method of placement and compaction, especially in elements with congested reinforcement or complex formwork.

Alternative tests such as the Vebe time or flow table may be used where appropriate. A mismatch between consistency and placement technique can result in segregation, poor consolidation, or incomplete coverage of reinforcement.

❖ *Chloride Content Class (CL 0.aa)*

Chloride content is a critical parameter in reinforced and prestressed concrete, as excessive chlorides can lead to corrosion of embedded steel, reducing structural durability. The standard specifies four classes:

- CL 0.20: suitable for prestressed or high-risk structures,

- CL 0.40: standard for reinforced concrete not exposed to frequent chloride ingress,
- CL 0.65 and CL 1.0: permitted only in unreinforced or specialized cases.

The value represents the maximum chloride ion content, expressed as a percentage of the mass of cementitious materials.

❖ *Optional Parameters*

In addition to the basic parameters described above, further specifications may be included to satisfy particular project requirements or exposure conditions. These may include:

- Minimum or target binder content (kg/m³),
- Maximum water-to-binder ratio,
- Type and class of cement (e.g., CEM I, CEM III/A),
- Use of supplementary cementitious materials (e.g., fly ash, slag),
- Air entrainment for resistance to freeze–thaw cycles.

These optional parameters are especially important in severe exposure classes such as XF4, XS3, or XA3, where performance-based validation may be required to justify deviations from prescriptive limits.

⇨ The BPS designation system under NF EN 206-1 provides a comprehensive and standardized method for specifying structural concrete with performance-based criteria. Each parameter; whether related to strength, environmental exposure, workability, or chemical resistance, contributes to ensuring that the concrete will fulfill its intended function over the full-service life of the structure. This designation not only facilitates clear communication between designers, producers, and contractors but also supports compliance with European and national regulations for structural safety, durability, and sustainability.

V.3 Influence of Design Parameters on Carbon Footprint

While the standardized designation of BPS concrete under NF EN 206-1 provides clarity in terms of mechanical and durability performance, these parameters have a significant and varying impact on the carbon footprint of the concrete. In particular, three parameters, cement type, strength class, and exposure class, play a dominant role in determining the overall environmental impact of a mix.

Cement Type: A Key Driver of Carbon Emissions

Among all the constituents of concrete, cement is by far the most carbon-intensive material. The choice of cement type has a direct influence on the embodied CO_2 per cubic meter of concrete.

According to findings synthesized by Infociment (2018), the carbon footprint varies substantially across different cement types:

- CEM III/B has the lowest carbon footprint, primarily due to its high content of ground granulated blast furnace slag (GGBFS), which substitutes for clinker.
- This is followed by CEM III/A and CEM V/A, which also incorporate significant proportions of supplementary cementitious materials (SCMs).
- CEM II/B and CEM II/A exhibit higher carbon content due to lower SCM substitution.
- CEM I, composed almost entirely of clinker, has the highest CO_2 emissions per unit.

The substitution of clinker with SCMs in composite cements significantly reduces emissions by lowering the energy-intensive calcination process. Therefore, for equivalent mechanical performance and durability, choosing a lower-emission cement can drastically reduce the environmental burden of the concrete.

Compressive Strength Class: Higher Performance, Higher Impact

When the cement type and exposure class are held constant, increasing the compressive strength class of the concrete generally leads to a proportional increase in CO_2 emissions. This is because higher strength levels require: greater binder content (primarily cement), lower water-to-binder ratios, tighter quality control and potential use of high-performance additives. For example, a concrete of class C60/70 will typically have a significantly higher carbon footprint than one of class C16/20, even when using the same cement and exposure class. This is especially critical in mass applications such as foundations or slabs, where strength beyond the structural requirement may offer little added value but significantly increase environmental costs.

Exposure Class: Indirect Influence via Prescriptive Requirements

Although the exposure class primarily addresses durability concerns, it also indirectly affects the carbon footprint by imposing prescriptive limits on mix design parameters. For more aggressive exposure conditions (e.g., XS3, XF4, XA3), standards may require: higher cement contents, lower water-to-cement ratios, specific types of binders or air-entraining agents. These additional constraints can lead to increased environmental impact compared to milder classes (e.g., XC1, X0) even when strength and cement type remain constant.

Interpretation Caution: Incomparable Mixes

It is essential to emphasize that comparing the carbon footprint of concretes with different combinations of strength class, cement type, and exposure class is not valid. Each parameter is interdependent and context-specific. For instance:

- A concrete with CEM III/B, exposure class XC1, and strength class C25/30 cannot be meaningfully compared to one with CEM I, exposure class XF4, and strength class C40/50.
- Any differences in CO_2 emissions may stem from multiple overlapping factors, not just cement type or strength level.

This principle is critical for the valid interpretation of results in the section 4.B.VI, where BPS concrete formulations are evaluated in a real-world application by Eiffage. Misinterpretation of emissions data due to unaligned parameters would undermine the reliability of the analysis and its conclusions.

V.4 Diversity of Concrete Mix Designations and Data Granularity

In practice, the data received from suppliers exhibited significant heterogeneity in both format and precision. While the ideal scenario, complete BPS designations aligned with the NF EN 206-1 standard, served as a reference point, the actual datasets spanned a wide spectrum of completeness, technical detail, and terminology. Some suppliers provided well-structured performance-based formulations such as *Agilia Prémurs C25/30 II/A CP2+LA D11 SF1 600 XC1 CL0.40* or *Articimo® Boucharde C25/30 CEM II/A 42.5 R CE CP2 NF DMax 20 S3 XF2 CL 0.65*, which included parameters such as compressive strength class, consistency, exposure class, maximum aggregate size, and chloride content. In these cases, the type of cementitious binder, for example, CEM II/A, was also explicitly specified, enabling more accurate estimation of environmental impacts.

In contrast, other suppliers submitted only partial or internal code-based entries, such as ACC-1-C16-XXX-X0-G3-N-BASE-001-S3-0. While such codes are not inherently unusable, they typically require additional interpretation. For instance, C16 refers to the compressive strength class, BASE can indicate the use of a CEM II-type cement, and S3 denotes the consistency class, yet these components are not standardized across suppliers and are often undocumented externally. This lack of formalization makes it difficult to automate processing or compare datasets without in-depth domain knowledge. Consequently, a dedicated pre-processing phase is required to decode and harmonize these entries, involving the translation of supplier-specific nomenclature into standardized parameters consistent with the NF EN 206-1 framework. Without this step, technical and environmental analyses would be based on inconsistent or incomplete information.

In some cases, datasets consisted solely of commercial product names or unit pricing without any corresponding information on volumes or material composition. In others, only volume and price were available, with technical characteristics entirely absent. This variability reflects both the disparate internal data architectures used by suppliers and the absence of a standardized reporting framework across the industry. Consequently, substantial effort was required to clean, standardize, and align the data to ensure analytical consistency. The stratified levels of data quality and technical completeness

are summarized in Figure 4-17, which illustrates the gradient from fully detailed and specification-rich records to minimal entries limited to price only, or price with volume but lacking any technical specification.

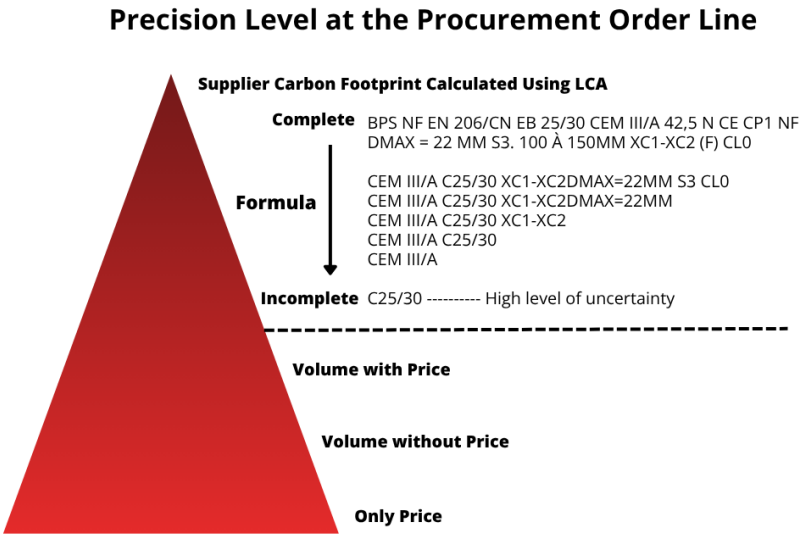


Figure 4-17 Typology of Concrete Mix Data Received from Suppliers: From Full BPS Specifications to Price-Only Records

The current state of supplier reporting is further illustrated in Table 4-6, which highlights the inconsistencies in the provision of key data fields such as mix formula, price, volume, and carbon footprint indicators (both per order and per cubic meter). In this context, a "complete" mix formula is defined as one that complies with the NF 206 standard, including all relevant characteristics such as cement type, strength class, exposure class, and any applicable treatment. Conversely, an "incomplete" formula refers to cases where only partial technical information is available, such as only the cement type, strength, or exposure class, without the full specification required for performance-based or environmental assessments. This minimum set of parameters is essential, as it directly determines the carbon intensity of the mix and is the main driver of CO_2 emissions in concrete production.

Table 4-6 Consistency of Technical and Environmental Data Reporting Across Suppliers

	Formula	Price	Volume	CO2eq data
Supplier 1	Complete	X	X	
Supplier 2	Incomplete		X	
Supplier 3	Complete		X	X
Supplier 4	Complete		X	X
Supplier 5	Incomplete		X	X
Supplier 6	Complete	X	X	
Supplier 7	Complete		X	
Supplier 8	Complete		x	

While some suppliers provide comprehensive information enabling environmental performance assessments, others only report partial data, often limited to pricing or order volumes without technical or environmental metrics. Notably, even among suppliers classified as delivering "complete"

mix formulas, the accompanying environmental data (e.g., CO_2eq per m^3) is not consistently available. This table underscores the fragmented and non-standardized nature of current supplier data practices, reinforcing the necessity for a harmonized reporting framework that mandates the inclusion of both technical and environmental specifications to support accurate life-cycle assessments and data-driven decision-making.

V. Problem Statement: Limitations of Current Procurement-Based Carbon Accounting

Accurately quantifying Scope 3 emissions within procurement processes remains a complex challenge, despite increasing digitalization and the adoption of carbon accounting frameworks. The LODACE platform, currently used within Eiffage to support emission tracking in purchasing activities, represents a significant advancement. However, several structural and methodological limitations constrain its ability to support a robust and integrated hybrid accounting model.

First, the platform still relies predominantly on monetary emission factors denominated in 2002 U.S. dollars, a legacy reference that introduces distortions when adjusted for inflation, currency fluctuations, and evolving material prices. This outdated baseline undermines the temporal and financial comparability of emissions estimates, especially as procurement and supply chain dynamics evolve in non-linear, sector-specific ways.

Second, and more critically, LODACE does not integrate supplier-specific emissions data. All suppliers within a given material category are treated as if they share a uniform carbon profile, ignoring the significant variability in emissions intensity linked to production methods, raw material sourcing, and geographic location. Even when supplier-level data is available, whether through voluntary disclosure, surveys, or targeted studies, the platform lacks a mechanism to structurally incorporate this differentiated information into its reporting engine or decision-making tools. As a result, emissions estimates are both generalized and static, limiting their utility for supplier engagement, benchmarking, or preferential sourcing based on environmental performance.

Third, inconsistencies persist even when applying more advanced modeling approaches. Both the top-down monetary model (Section 4.A.I) and the bottom-up physical model (Section 4.A.III) produce noticeable disparities in emissions estimates, as illustrated in Figure 4-15. For instance, the top-down method underestimates emissions for several high-volume concrete mixes by 15–40% compared to bottom-up benchmarks. Conversely, certain specialty concretes show higher emissions in the bottom-up model, falling outside the interquartile range of the monetary estimates. These discrepancies indicate that data granularity alone is not sufficient; achieving convergence across models requires harmonized conversion factors, unit consistency, and alignment of system boundaries. Without this, divergent results may compromise the interpretability and reliability of Scope 3 calculations.

Fourth, beyond the limitations of the platform itself, additional constraints emerged from the process of collecting and processing supplier data. The data received varied widely in structure, terminology, and completeness. Significant manual effort was required to decode internal product codes, harmonize nomenclature, and translate heterogeneous entries into standardized performance descriptors aligned with NF EN 206-1. This preprocessing phase, although essential, proved time-consuming and highly dependent on expert judgment, making it difficult to scale across projects or replicate consistently.

Fifth, in the absence of detailed formulation data, emissions factors were frequently calculated using yearly average prices for ready-mix concrete, regardless of differences in technical specifications such as cement type, compressive strength, or chloride content. This simplification, while practical, introduces inaccuracies by assuming homogeneity in the carbon intensity of materials that are, in practice, highly differentiated. In effect, financial proxies are used as stand-ins for physical and environmental performance, leading to systemic biases in Scope 3 accounting.

Together, these challenges highlight the disconnect between current procurement systems and the precision required for meaningful climate action. They underscore the urgent need for new methodologies capable of integrating supplier-specific, product-level data into operational decision-making. This research addresses that gap by proposing and testing a hybrid accounting framework designed to embed granularity, accuracy, and interoperability into industrial carbon tracking practices.

VI. Tailored Solution: Multi-Level Modeling Strategy for Incomplete Procurement Data

This section contributes to an article by Essouid et al., "Automated Data Processing for Procurement and Upstream Scope 3 Emissions Accounting: Evidence from a Ready-Mixed Concrete Case Study", which is currently under finalization.

To address the limitations identified in both the LODACE platform and the collected procurement data, this research proposes a systematic multi-tiered impact modeling strategy that adapts to varying levels of data completeness. This approach operationalizes the hybrid framework described in Section A by systematically determining the most suitable emissions estimation method based on the nature and quality of available information, ranging from prices and volumes to technical specifications and supplier carbon disclosures.

The modeling logic is organized into sequential decision points:

- When concrete mix formulas are available and complete, a preprocessing step is conducted to decode and standardize the entries. Internal codes or descriptive strings (e.g., ACC-1-C25-XXX-XF1-G3) are translated into structured parameters (e.g., compressive strength, cement type, exposure class), allowing for refined LCI matching or customized modeling. After formula

standardization, when concrete mix formulas have been decoded into structured parameters, emissions modeling can be carried out based on the availability of environmental data.

- If supplier-specific emissions data are available alongside technical formulations, it becomes possible to calculate accurate physical emission factors, (kg CO_2e per m^3) based on the structured procurement data. These emission factors can then be integrated into the LODACE platform, disaggregated by supplier, business unit (BU), regional division (DR), or operational branch (BR). This allows for supplier-level tracking, regional benchmarking, and more granular carbon accounting within the organization → **Suppliers 3, 4 and 5**
- When emissions data are not available, two alternative modeling routes are pursued based on the available procurement information:

- Volume → Apply specific LCI-based emission factors (kg CO_2e/m^3) tailored to the material characteristics → **Suppliers 7 and 8**
- Volume + price → Calculate unit cost per m^3, which can be stored for future use when only price is known. This creates a feedback loop that enriches the price-only model with embedded material-specific emission logic → **Suppliers 1 and 6**

- When concrete mix formulas are unavailable:
  - When volume data is available, bottom-up modeling is preferred, applying emission factors from LCI databases. This provides more accurate results by linking physical quantities (e.g., m^3 of ready-mix concrete) to representative environmental processes.
  - When only price data is available, environmental impacts are estimated using top-down monetary emission factors derived from EXIOBASE, aligned via the economic sector (NAF classification). This enables an approximate but scalable attribution of emissions when physical or technical information is missing.

This logic is fully integrated into the hybrid decision framework introduced in Section A, where procurement records are routed through a structured decision tree to select the most appropriate modeling tier. Whether using bottom-up physical quantities, supplier-level disclosures, or fallback monetary intensities, the proposed solution ensures consistency and data-driven adaptability. It bridges the gap between theoretical LCA rigor and real-world procurement constraints, enabling progressive refinement as better data becomes available.

VI.1 Preprocessing Concrete Formula Data

When supplier files contain unstructured concrete mix formulas, a preprocessing workflow is applied to transform dense strings or internal codes into structured, model-ready data. These formulas must be decoded into six key technical attributes: cement type, compressive strength class, maximum aggregate size, exposure class, consistency class, and chloride content class.

The process, shown in Figure 4-18, begins by removing irrelevant rows, such as those labeled "Administrative Fees" or "Contribution", using a regular expression and a customizable keyword list. The cleaned dataset is then scanned to catalog supplier-specific terminology, identifying variations like "CEM II", "CEM 2", or "II" for cement type, and "16 MPa" or "C16/20" for strength class. This curated reference set supports the extraction phase, where a Python function maps known terms in each formula to structured parameters.

Finally, the extracted values are harmonized to NF EN 206+A2/CN standards using a replacement dictionary (e.g., converting "CL0,4" to "CL 0.4"). The result is a standardized dataset that enables consistent classification, filtering, and environmental modeling. Table 4-7 illustrates the transformation of 25 randomly selected entries from over 34,000 raw records collected in 2024.

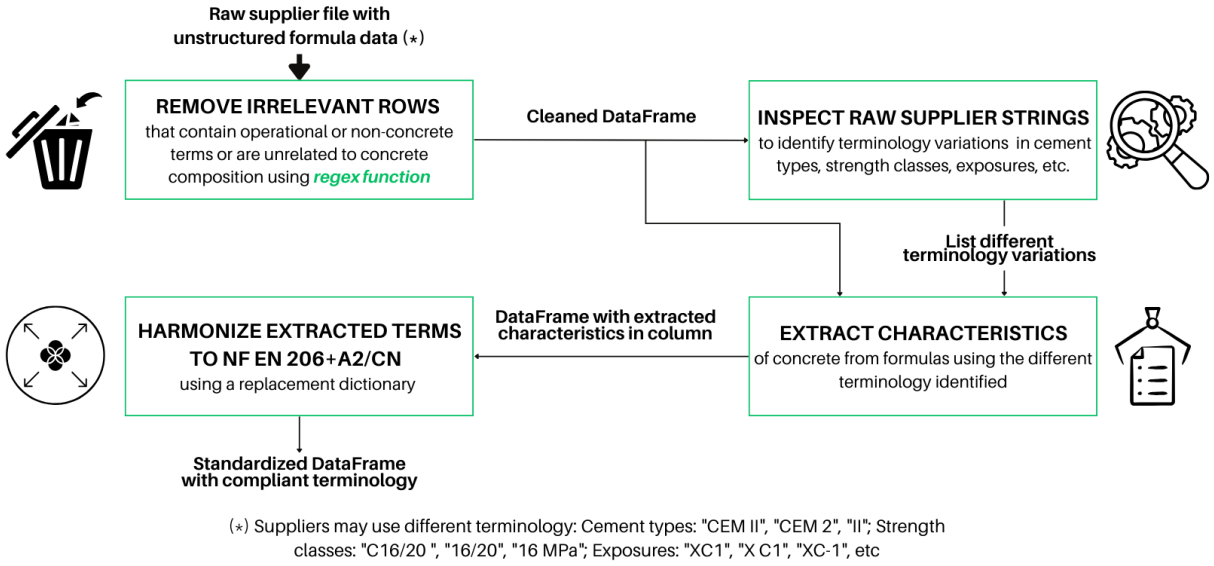


Figure 4-18 Workflow for Preprocessing and Standardizing Unstructured Concrete Mix Formulas into Model-Ready Parameters

This approach is both practical and generalizable. It relies on flexible, transparent steps, regex-based filtering, dictionary-driven extraction, and harmonization, that can be easily adapted to new suppliers, datasets, or even to other construction materials beyond concrete. The system is modular and scalable, making it suitable for large-scale data processing or integration into automated pipelines. Moreover, its maintainability allows for easy updates to the reference terminology, ensuring continued relevance as market conventions evolve.

VI.2 Supplier-Specific Emission Factor Modeling for Operational Integration and Decision-Making

To enable precise, supplier-level carbon performance monitoring, a structured methodology was developed to compute physical emission factors expressed in kilograms of CO_2 equivalent per cubic meter (kg CO_2e/m^3). This modeling process is applied to procurement records that contain both detailed concrete mix specifications and associated emissions data. It forms a key operational tier

within the broader hybrid modeling strategy introduced earlier and is intended to support integration into the LODACE platform. The resulting data allow for granular disaggregation by supplier, and when metadata are available, by organizational layers such as business units (BU), regional divisions (DR), or operational branches (BR). Figure 4-19 illustrates the computational workflow used to derive supplier-specific emission intensities from raw procurement data, encompassing data preparation, aggregation, normalization, and supplier ranking.

The workflow begins with a data cleaning phase in which procurement records are reformatted and validated for analytical consistency. This includes formatting adjustments such as the removal of leading or trailing whitespace, as well as the conversion of key quantitative fields, specifically volume and CO_2 emissions per order, into valid numeric data types suitable for computation. Once prepared, the dataset is filtered to retain only entries that contain actual emissions data, ensuring that subsequent modeling is grounded in verifiable carbon information rather than assumptions.

Following this, the emissions-enriched records are aggregated by both supplier identity and technical characteristics of the concrete formulation. These characteristics include cement type, compressive strength class, maximum aggregate size, exposure class, consistency class, and chloride content class. If the procurement data also contains internal organizational codes (e.g., branch, BU, or DR), the aggregation logic can be extended to incorporate these attributes, enabling even finer-grained analysis. For each supplier-formula grouping, total emissions and volume are summed to form the basis for calculating specific carbon intensity values.

Emission intensity is computed by dividing the total CO_2 emissions by the total volume delivered for each supplier-formula combination. This yields a normalized metric (kg CO_2eq/m^3) that reflects the embodied carbon of each mix configuration in a directly comparable format.

Table 4-7 Transformation of Unstructured Concrete Mix Formulas into Standardized Technical Attributes (Sample Output)

Input	**Output**					
Raw supplier file with unstructured formula data	**Cement Type**	**Compressive Strength Class**	**Maximum Aggregate Size**	**Exposure Class**	**Consistency Class**	**Chloride Content Class**
BPS XC1 (F) C30/37 S3 Cl 0,40 Dmax=20 CEM I	CEM I	C30/37	DMAX20	XC1	S3	CL 0,4
F.65 C35/45 350 I 52,5N SR5-PM D12 S180 XF2-XC4 E/C<0,4	CEM I	C35/45	DMAX12	XC4-XF2	S1	-
VRD 350 Base S1 Dmax=20	CEM II	C25/30	DMAX20	-	S1	-
ECOPact Fluide C40/50 D11 S4 XF1 (NAF3)	-	C40/50	DMAX11	XF1	S4	-
EB propreté C16/20 CEM II/A-L 42,5 R CE CP2 NF DMax 20 S4 X0 CL 0.4	CEM II/A	C16/20	DMAX20	X0	S4	CL 0,4
EB Départ C25/30 330 KG/M3 CEM II/A-LL 42,5 R CE CP2 NF DMax 16 S1 XC1 CL 0.4	CEM II/A	C25/30	DMAX16	XC1	S1	CL 0,4
EB Voirie C30/37 CEM II/A-L 42,5 R CE CP2 NF DMax 20 S3 XF3 CL 0.4	CEM II/A	C30/37	DMAX20	XF3	S3	CL 0,4
ECOPact Voiles C25/30 II/B D22 S3 XC1	CEM II/B	C25/30	DMAX22	XC1	S3	-
LB Fluide C25/30 II/B 52,5N D16 S4 XC1 CL0,40	CEM II/B	C25/30	DMAX16	XC1	S4	CL 0,4
ECOPact C25/30 II/B 42,5R CP2 D14 S3 XF1	CEM II/B	C25/30	DMAX14	XF1	S3	-
BPS C25/30 II/B 42,5N CP1 CP S3 XF1	CEM II/B	C25/30	-	XF1	S3	-
EB Ouvrage d'art C30/37 CEM II/B-S 42,5 N CE CP1 NF DMax 20 S3 XF1 CL 0.4	CEM II/B	C30/37	DMAX20	XF1	S3	CL 0,4
EB Voile C40/50 CEM II/C-M (S-L) 42,5 N NF DMax 22.4 S3 XF1 CL 0.4	CEM II/C	C40/50	DMAX 22,4	XF1	S3	CL 0,4
EB Voile fluide C25/30 CEM II/C-M (S-L) 42,5 N NF DMax 12 S4 XC1 CL 0.4	CEM II/C	C25/30	DMAX12	XC1	S4	CL 0,4
EB Fondation fluide C25/30 CEM II/C-M (S-L) 42,5 N NF DMax 20 S4 XC1 CL 0.4	CEM II/C	C25/30	DMAX20	XC1	S4	CL 0,4
BPS XA1 (F) C30/37 S3 Cl 0,65 Dmax=20 CEM III +acc	CEM III	C30/37	DMAX20	XA1	S3	CL 0,65
EB Fondation SP C35/45 CEM III/A 42,5 N LH CE PM ES CP1 NF DMax 20 S3 XA2 CL 0.65	CEM III/A	C35/45	DMAX20	XA2	S3	CL 0,65
EB Ouvrage d'art fluide C35/45 CMIN 350 KG/M3 CEM III/A 42,5 N LH CE PM ES CP1 NF DMax 22.4 S18 XA2 CL 0.65	CEM III/A	C35/45	DMAX22	XA2	S1	CL 0,65
LB Chape C25-F5 400 FPP III/B 42,5N SR-PM CP1-LH D2 S1	CEM III/B	C25/30	DMAX2	-	S1	-
Ultra R sol C25/30 CEM III/C 32,5 N-LH/SR CE PM NF DMax 22.4 S3 XC1 CL 0.65	CEM III/C	C25/30	DMAX 22,4	XC1	S3	CL 0,65
Agilia Vertical COL C25/30 V/A 42,5N PMES CP1 D16 SF 670 XF	CEM V/A	C25/30	DMAX16	XF	-	CL 0,4
LB Fluide C30/37 V/A 42,5N D16 S4 XC1 XC2 CL0,40	CEM V/A	C30/37	DMAX16	XC1-XC2	S4	CL 0,4
Agilia Vertical C25/30 V/A 42,5N D16 SF 720 XF1	CEM V/A	C25/30	DMAX16	XF1	-	-
BPS C30/37 V/A 42,5N D22 S3 XF1 CL0,40	CEM V/A	C30/37	DMAX22	XF1	S3	CL 0,4
C25/30 V/A 42,5N PMES CP1 D22 S1 R0T1	CEM V	C25/30	DMAX22		S1	

These values are then rounded to three decimal places to enhance interpretability and standardization across reports. The resulting dataset provides a robust, empirical basis for benchmarking suppliers not only against market averages but also against one another for equivalent concrete types.

To support procurement optimization and low-carbon decision-making, the final step involves isolating the best-performing supplier for each distinct combination of cement type, compressive strength class, and exposure class. By identifying the supplier with the lowest emission intensity within each of these standard configurations, the organization gains a decision-ready shortlist of optimal sourcing options. This enables informed trade-offs between cost, performance, and environmental impact to be evaluated with transparency and consistency.

The resulting dataset is exported in a structured format compatible with the LODACE platform (CSV). Once integrated, the emission factors can be linked to internal procurement hierarchies, enabling region-specific benchmarking, supplier evaluation, and support for carbon reduction strategies across the value chain.

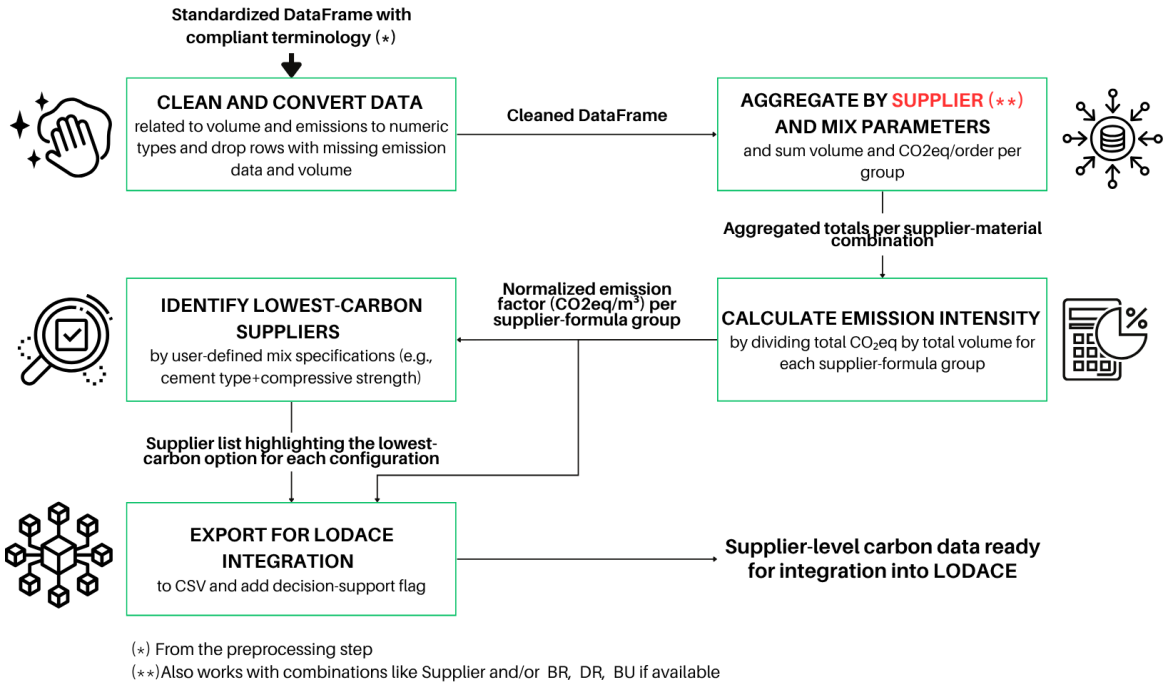


Figure 4-19 Workflow for Computing Supplier-Specific CO_2 Emission Factors (kg CO_2e/m^3) from Procurement Data

Table 4-8 presents the results of the emissions modeling process, where CO_2 emission intensity (expressed in kg CO_2e/m^3) is calculated for each supplier-formula combination by dividing the total reported emissions by the total volume delivered. These values form the basis for benchmarking the carbon performance of different concrete suppliers across varied technical specifications.

To support procurement optimization, Table 4-9 provides a filtered view showing only the lowest-emitting supplier for each mix configuration.

Table 4-8 Computed Emission Intensities per Supplier and Mix Configuration (Sample)

Supplier	Cement Type	Compressive Strength Class	Maximum Aggregate Size	Exposure Class	Consistency Class	Chloride Content Class	Total volume	Total CO2eq	Kg CO2eq/m3
Supplier 3	**CEM I**	**C30/37**		**XF1**	**S3**	**CL 0,4**	**16.5**	**4100.05**	**248.488**
Supplier 3	CEM II/A	C25/30		XC1	S1	CL 0,4	4.25	898.96	211.52
Supplier 3	CEM II/B	C30/37	DMAX2	XD2	S3	CL 0,4	1.5	344.57	229.713
Supplier 3	CEM II/C	C20/25		XC1	S1	CL 0,4	459.15	61288.09	133.482
Supplier 3	CEM III/A	C25/30		XC1	S4	CL 0,65	104	11766.41	113.139
Supplier 3	CEM III/A	C40/50		XF1	S3	CL 0,65	42.5	6523.29	153.489
Supplier 4	CEM I	C35/45	DMAX10	XF4	S3		1	308	308
Supplier 4	**CEM I**	**C30/37**	**DMAX22**	**XF1**	**S3**		**4**	**941**	**235.25**
Supplier 4	CEM II	C16/20	DMAX22	X0	S4		2	291	145.5
Supplier 4	CEM II/A	C20/25	DMAX12		S1		2	309	154.5
Supplier 4	CEM II/B	C16/20	DMAX10	X0	S1	CL 0,4	4	398	99.5
Supplier 4	CEM III/A	C25/30	DMAX16	X0	S1		2	164	82
Supplier 4	CEM III/B	C25/30	DMAX11	XF2	S2		3	487	162.333
Supplier 4	CEM V/A	C25/30	DMAX22	XC1	S3	CL 0,4	7	977	139.571
Supplier 5	**CEM I**	**C30/37**	**DMAX22**	**XF1**	**S4**		**1534.5**	**423328.5**	**275.874**
Supplier 5	CEM II	C25/30	DMAX22	XF1	S4		35	8435	241

Table 4-9 Lowest-Emission Suppliers per Concrete Mix Configuration (Sample)

Cement Type	Compressive Strength Class	Exposure Class	Supplier	CO2eq/m3	Is_Lowest_Emitter
CEM I	**C30/37**	**XF1**	**Supplier 4**	**235.25**	**True**
CEM II/A	C35/45	XD3	Supplier 3	248.143	True
CEM II/B	C30/37	XF2	Supplier 4	152.615	True
CEM III	C30/37	XA1	Supplier 4	129.857	True
CEM III/B	C25/30	X0	Supplier 4	55.5	True

The grouping was performed using three key technical parameters, cement type, compressive strength class, and exposure class, which represent the minimum specification set known to significantly influence the carbon footprint of concrete. This sample output illustrates the selection logic used to identify top-performing suppliers for low-carbon procurement within the organization.

As explained in Section 4.B.V.3, a valid comparison between concrete mixes in terms of carbon footprint requires that the cement type, strength class, and exposure class be identical. Only under these aligned conditions can differences in CO_2 emissions be meaningfully attributed to supplier performance or mix optimization.

In Table 4.8, we observe that for CEM I – C30/37 – XF1, the carbon emissions vary among suppliers:

- Supplier 3: 248.388 $kgCO_2$ eq/m^3,
- Supplier 4: 235.250 $kgCO_2$ eq/m^3,
- Supplier 5: 275.874 $kgCO_2$ eq/m^3.

Thus, Supplier 4 demonstrates a lower emission factor within the same concrete specification, as also highlighted in Table 4.9.

However, claiming that Supplier 4's CEM III/A – C25/30 – XC1 concrete is environmentally superior to CEM I – C30/37 – XF1 is neither valid nor justified. These products are fundamentally different in terms of mechanical performance and durability requirements and are designed for distinct structural and environmental conditions. Comparing them directly disregards their respective functional roles and violates the principles of fair and meaningful carbon benchmarking.

In cases where volume data are unavailable but unit prices for concrete mixes are known, the same computational logic can be applied to derive monetary emission factors (expressed in kg CO_2e/€). By dividing the total CO_2 emissions by the total cost associated with each supplier-formula combination, a spend-based carbon intensity can be estimated. This alternative metric aligns with the structure of top-down models and enables integration into procurement systems that track costs more reliably than physical volumes. While less precise than physical intensity values (kg CO_2e/m^3), these monetary emission factors remain valuable for comparative benchmarking and high-level carbon performance screening when integrated prices reflect real product configurations

VI.3 Bottom-Up Volume-Based Estimation of Supplier-Level Emissions Using BETie-Derived LCI Factors

To operationalize Scope 3 emission quantification at the supplier level, we applied a structured bottom-up matching process that integrates normalized procurement data with emission factors sourced from BETie (Béton et Impacts Environnementaux), a dedicated life cycle modeling tool for

ready-mix concrete (SNBPE, 2024). This approach builds on the preprocessing workflow outlined in Section 4.B.VI.1, where procurement data were cleaned, standardized according to NF EN 206+A2/CN terminology, and aggregated by supplier and mix configuration.

The emission factors used in this step are drawn from the BETie database (see Appendix 4-1), which provides granular environmental impact values (in kg CO_2e per m^3) based on specific mix formulations. BETie enables users to generate simplified or EPDs conforming to European standards, including the EN 15804+A2. It accounts for the full life cycle of ready-mix concrete products, covering upstream material sourcing, transport, implementation, use phase, and end-of-life, along with recycling potential. BETie emission profiles are mainly sensitive to cement type, strength class, exposure class, and additional formulation-specific parameters (e.g., chloride resistance, maximum aggregate size).

For the proposed operational modeling, a minimum of three technical parameters, cement type, compressive strength class, and exposure class, were required to retrieve the appropriate emission factor. The BETie reference table was structured such that each row combines a strength-exposure class grouping and associated emission factors per cement type. A matching algorithm was developed to identify rows in the BETie dataset where the compressive strength matches exactly and the exposure class appears within the defined exposure combination (e.g., "XC1" in "XC1-XC2"). The logic was embedded in a lookup function that returns the emission factor for each supplier-mix configuration.

Figure 4-20 summarizes the full computational workflow, from the cleaned input dataset to the estimation of total emissions.

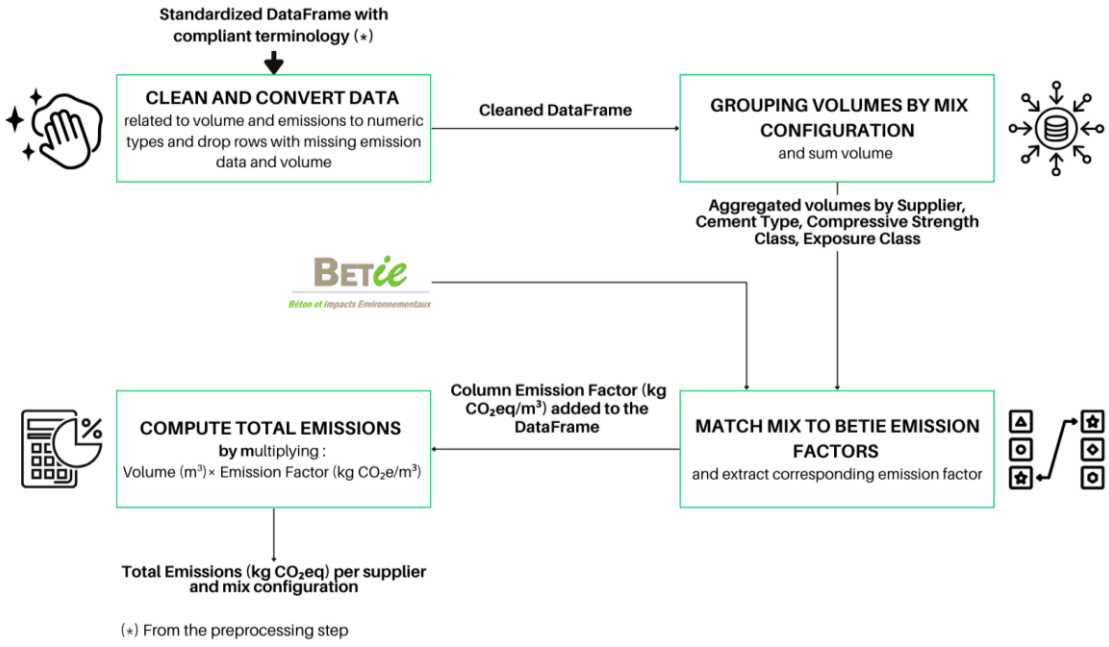


Figure 4-20 Integration of BETie Emission Factors into Supplier-Level Scope 3 Modeling

To validate the implementation and test its consistency, Supplier 7, a representative actor with a large and diverse dataset, was selected as a case study. This validation ensured that the algorithm was capable of accurately retrieving and applying emission factors across a variety of concrete formulations. Table 4-10 presents a sample output showing the integration of BETie-derived emission factors into procurement records. Each row represents a unique combination of cement type, compressive strength, and exposure class, along with the corresponding procurement volume, emission factor, and computed total emissions.

Table 4-10 Sample Output of Bottom-Up Volume-Based Emission Modeling Using BETie for Supplier 7

Cement Type	Compressive Strength Class	Exposure Class	Volume	Emission Factor (kg CO2e/m^3)	Total Emissions (kg CO2e)
CEM I	C20/25	XC1	12.5	213	2662.5
CEM I	C30/37	XA1	695.5	270	187785
CEM I	C30/37	XF1	75	229	17175
CEM II/A	C20/25	XC1	22.5	191	4297.5
CEM II/A	C30/37	XC4	111.5	205	22857.5
CEM II/A	C35/45	XF1	4980.1	242	1205184.2
CEM II/B	C20/25	XC1	126.5	165	20872.5
CEM II/B	C30/37	XC1	773.5	177	136909.5
CEM II/B	C40/50	XC1	36	239	8604
CEM III/A	C25/30	XF1	62.2	137	8521.4
CEM III/A	C40/50	XA3	195.8	179	35048.2
CEM V/A	C25/30	XC2	106	140	14840
CEM V/A	C35/45	XA2	80.4	188	15115.2
CEM V/A	C40/50	XA3	75.8	196	14856.8

VI.4 Integrating Weighted Average Price Modeling into LODACE for Scope 3 Precision

One of the primary challenges in Scope 3 emissions accounting lies in the over-reliance on average prices for ready-mix concrete, typically reported on an annual basis without regard for the underlying technical characteristics of the materials. In many cases, the absence of detailed formulation data has led to the use of aggregated yearly average prices, such as 110 euros per cubic meter reported by the sustainability department of Eiffage Group for the year 2024. While this approach offers a convenient proxy for emission estimation, it assumes homogeneity in the carbon intensity of all concrete mixes, thereby introducing substantial inaccuracies. Such simplifications obscure the variation in embodied carbon across different cement types, compressive strength classes, and durability specifications. Consequently, financial proxies are often misapplied as stand-ins for physical or environmental performance, reinforcing systemic biases in Scope 3 carbon accounting.

To address this issue, a structured pipeline was developed to transform raw commercial data into decision-support metrics that are both cost-aware and technically specific (Figure 4-21). The process

begins with the ingestion of a standardized DataFrame that has undergone preprocessing to ensure consistency in terminology and formatting. Price and volume data are then cleaned and converted into numeric types, and rows with missing or invalid values are excluded. This results in a cleaned dataset in which each entry reliably represents a delivered quantity of concrete with associated commercial terms.

Next, the data are aggregated according to supplier, client, and key mix parameters such as cement type, compressive strength class, and exposure class. This aggregation enables the computation of total delivered volume and total price for each supplier-client-material combination. A weighted average price per cubic meter is then calculated for each combination. This value reflects the actual unit cost associated with each specific material configuration and supplier, as procured within a specific BU, BR, or DR.

It is also important to note that for the same technical configuration and supplier, prices may vary between different regional divisions or business units. These discrepancies are not the result of material differences but are instead driven by localized pricing agreements and negotiated contracts between the supplier and the regional procurement teams. Factors influencing these variations include order volume, delivery frequency, project scale, and historical supplier relationships within a specific regional division. As such, the same supplier may offer different prices to different branches of the organization for identical concrete specifications. This underlines the importance of maintaining regional granularity in pricing analysis, as aggregating prices at the national level without accounting for regional negotiation dynamics could mask important cost-saving or procurement insights.

Following this, the supplier offering the lowest weighted average price is identified for each unique combination of client, cement type, compressive strength class, and exposure class, as these represent the minimum technical specifications commonly provided by all suppliers. This step supports procurement optimization by highlighting the most cost-effective supplier while still preserving the required technical attributes of the mix. The results are then exported for integration into LODACE. These exports are designed to enhance both the precision and utility of Scope 3 calculations by grounding emissions factors in real commercial behavior rather than generalized estimates.

Critically, this architecture introduces a feedback loop for future data use. When both price and volume are known, the calculated unit cost per cubic meter can be stored and indexed to its technical and commercial context. In subsequent cases where only price is available, this enriched historical database enables the system to infer likely mix compositions and corresponding emissions, enhancing accuracy in data-scarce situations. This forward-compatible logic transforms basic financial records into tools for material-specific carbon tracking and decision support.

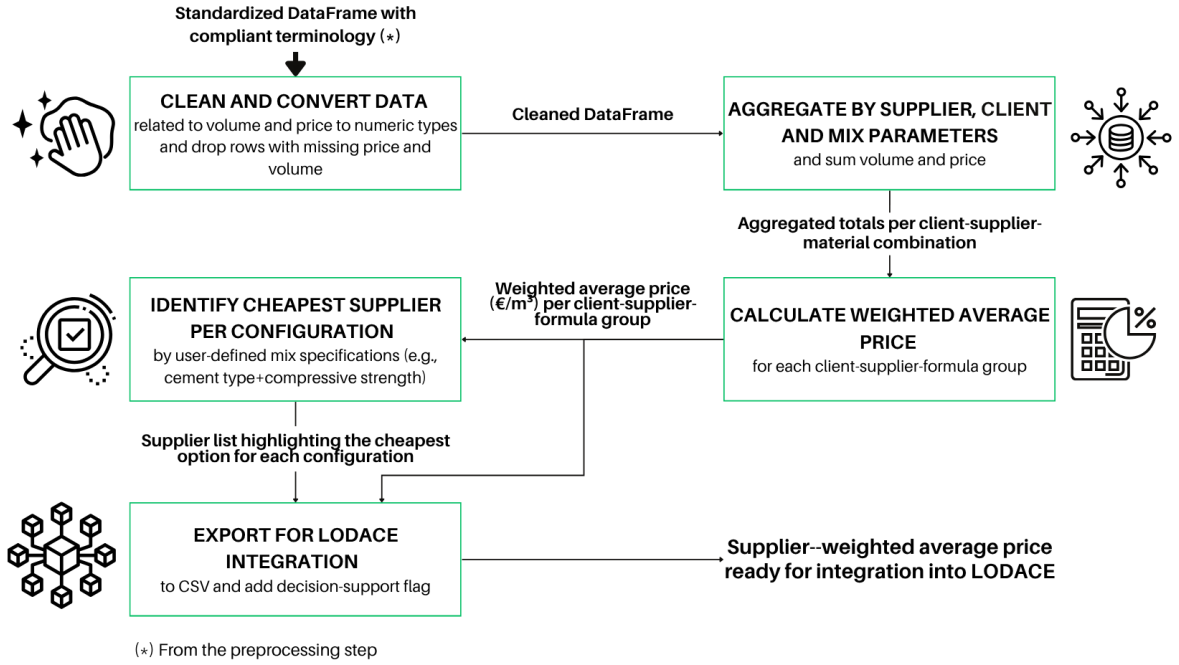


Figure 4-21 Architecture of Weighted Average Price Calculation and Supplier Optimization Workflow

The results in Tables 4-11 and 4-12 are drawn from a representative sample of the full dataset, used to demonstrate the functionality and relevance of the automated analysis. Table 4-11 presents the volume-weighted average price for each supplier, calculated per unique configuration and Eiffage Business Region (BR) or Division (DR). This approach ensures that price comparisons consider the actual volume delivered, avoiding bias from low-volume outliers.

In Table 4-12, we identify the cheapest supplier for each division and technical configuration. The results show considerable price variation across suppliers for similar cement types and exposure classes. This highlights the need for data-driven supplier selection, as relying on default suppliers may lead to avoidable cost differences. The method allows each division within Eiffage to benchmark and optimize procurement choices based on real, weighted market data.

VI.5 Estimating Environmental Impacts in the Absence of Concrete Mix Formulas

In LCA studies applied to construction materials, particularly concrete, detailed knowledge of the mix composition is essential to obtain accurate environmental impact results. However, in real-world procurement and reporting contexts, concrete mix formulas are not always available. This limitation can arise due to confidentiality constraints, lack of supplier disclosure, or data incompleteness at early project stages. To address such gaps while maintaining continuity in environmental quantification, a dual modeling approach is implemented, tailored to the type of available data: monetary (price) or physical (volume).

Table 4-11 Sample of Weighted Average Prices per Configuration

Eiffage Division = Client	Supplier	Cement Type	Compressive Strength Class	Maximum Aggregate Size	Exposure Class	Consistency Class	Chloride Content Class	Total Price (€)	Total Volume (m^3)	Average Price (€/m^3)
EIFFAGE CONSTRUCTION IDF	Supplier 1	CEM III	C25/30	DMAX20	XC1	S3	CL 0,65	1255.99	14.5	86.62
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM III	C30/37	DMAX20	XC4	S3	CL 0,65	995	10	99.5
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM III	C30/37	DMAX20	XF1	S3	CL 0,65	3410	31	110
EIFFAGE CONSTRUCTION IDF	Supplier 1	CEM III	C40/50	DMAX20	XC3	S3	CL 0,65	1140	9.5	120
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM I	C30/37	DMAX20	XC1	S3	CL 0,4	409.5	4.5	91
EIFFAGE CONSTRUCTION GRAND PROJETS	Supplier 1	CEM I	C60/75	DMAX10	XF1	S4	CL 0,4	162	1	162
EIFFAGE CONSTRUCTION GRAND PROJETS	Supplier 1	CEM II	C25/30	DMAX10	XC1	S3	CL 0,4	432	4.5	96
EIFFAGE CONSTRUCTION IDF	Supplier 1	CEM II	C25/30	DMAX10	XF1	SF2	CL 0,4	1681.68	14	120.12
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM II	C40/50	DMAX20	XF3	S3	CL 0,4	3751	31	121
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM II	C50/60	DMAX10	XF1	S4	CL 0,4	7757.5	53.5	145
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM I	C25/30	DMAX20	XC1	S4		2396.25	22.5	106.5
EIFFAGE CONSTRUCTION BOIS	Supplier 6	CEM I	C25/30	DMAX22	XC1-XC2	S3		460	4	115
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM I	C25/30	DMAX20	XC1-XC2	S3		61032.3	594	102.75
EIFFAGE GENIE CIVIL	Supplier 6	CEM I	C35/45	DMAX20	XA2	S4		78556.5	621	126.5
EIFFAGE GENIE CIVIL	Supplier 6	CEM I	C35/45	DMAX20	XA2	S5		791025.75	6061.5	130.5
EIFFAGE FONDATIONS	Supplier 6	CEM II/A	C30/37	DMAX14	XC1	S4		1256.85	10.5	119.7
EIFFAGE FONDATIONS	Supplier 6	CEM II/A	C30/37	DMAX22	XC1	S4		1166.4	10	116.64
EIFFAGE GENIE CIVIL	Supplier 6	CEM III/A	C25/30	DMAX20	XC1	S3		16359	142.5	114.8
EIFFAGE GENIE CIVIL	Supplier 6	CEM III/A	C30/37	DMAX10	XF1	S2		5571	45	123.8
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM III/B	C16/20	DMAX22	X0	S3		781.5	7.5	104.2

Table 4-12 Sample of Cheapest Suppliers by Eiffage Division and Configuration

Eiffage Division = Client	**Cheapest Supplier**	**Cement Type**	**Compressive Strength Class**	**Exposure Class**	**Average Price (€/m^3)**
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM I	C60/75	XF1	169.47
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM II	C25/30	XC1	104.12
EIFFAGE CONSTRUCTION IDF TERTIAIRE	Supplier 1	CEM II	C40/50	XF3	121
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM I	C16/20	X0	101.24
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM I	C25/30	XC1-XC2	104.98
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM III	C30/37	XA1	123.51
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM III	C30/37	XF1	114.7
EIFFAGE CONSTRUCTION PICARDIE	Supplier 6	CEM III/B	C30/37	XA1	123.7
EIFFAGE CONSTRUCTION RESIDENTIEL	Supplier 1	CEM I	C40/50	XC1	114.38
EIFFAGE CONSTRUCTION RESIDENTIEL	Supplier 1	CEM I	C40/50	XF1	176.14
EIFFAGE CONSTRUCTION RESIDENTIEL	Supplier 1	CEM I	C80/95	XC1	236
EIFFAGE CONSTRUCTION RESIDENTIEL	Supplier 1	CEM III	C40/50	XC1	96
EIFFAGE GENIE CIVIL	Supplier 6	CEM I	C16/20	X0	122
EIFFAGE GENIE CIVIL	Supplier 6	CEM I	C40/50	XA2	130.51
EIFFAGE GENIE CIVIL	Supplier 6	CEM I	C50/60	XA3	130
EIFFAGE GENIE CIVIL	Supplier 6	CEM II/A	C20/25	X0	108
EIFFAGE GENIE CIVIL	Supplier 6	CEM II/A	C35/45	XC1-XF1	122.99

This section outlines two estimation approaches, top-down and bottom-up, which are integrated into the overall framework and used depending on data availability. These methods are operationalized through automated procedures presented in Section A, allowing consistent application across large datasets or diverse project portfolios.

VII.5.1 Price-Based Estimation: Top-Down Approach via EXIOBASE

When only economic data (e.g., prices or expenditures) are available, a top-down modeling approach is employed, grounded in EEIO analysis. This method leverages EXIOBASE 3.8, a global multiregional input–output database that links monetary flows to environmental emissions across sectors.

In this framework, ready-mixed concrete is mapped to the French economic activity code:

NAF 23.63Z – Fabrication de béton prêt à l'emploi ➔ (*Manufacture of ready-mixed concrete* in English)

Using the Impact World+ 2002 impact assessment method integrated with EXIOBASE 3.8, the emission factor assigned to this sector is: 2.0709 kg CO_2eq per € 2024.

This emission intensity allows for the estimation of climate impacts directly from expenditure, using the equation 4-4:

$$\boldsymbol{Emissions\ CO_2eq = Price}\ (€) \times \boldsymbol{2.0709\ kg\ CO_2eq/€2024}$$

Equation 4-4 Top-Down Emission Estimation for Ready-Mixed Concrete Using EXIOBASE

Although less precise than bottom-up methods, this approach is broadly scalable and rapidly deployable, enabling estimations even in early procurement phases or large datasets where mix-specific information is absent.

VII.5.2 Volume-Based Estimation: Bottom-Up Approach via LCI Databases

When physical quantities such as volumes (in m^3) are available, but mix designs remain unknown, a bottom-up approach is favored. This method applies emission factors derived from detailed Life Cycle Inventory (LCI) datasets, providing a more representative and material-specific estimate of environmental impacts.

In this case, ready-mixed concrete is associated with the French CPF classification:

CPF 23.63 – Béton prêt à l'emploi ➔ (*Ready-mixed concrete*)

The selected LCI process is extracted from ecoinvent 3.9.1, using the Impact World+ 2002 model as the impact assessment framework. The representative process used is: *"Concrete, all types, to generic market for concrete, normal strength".*

This results in a climate change emission factor of: 215.398 kg CO_2eq per m^3

Environmental impacts are thus calculated by multiplying the concrete volume by this emission factor (Equation 4-5):

$$\boldsymbol{Emissions\ CO_2eq = Volume\ (m^3) \times 215.398\ kg\ CO_2eq/m^3}$$

Equation 4-5 Bottom-Up Emission Estimation for Ready-Mixed Concrete Using Ecoinvent

This bottom-up method is preferred when volume data is present, as it links directly to physical flows and more accurately reflects real environmental burdens than financial proxies.

VII.5.3 Integration in the Analytical Framework

Both estimation approaches are fully integrated into the LCA automation pipeline, specifically within Model I (price-based) and Model III (volume-based). The decision logic embedded in the model selects the appropriate method dynamically, depending on data availability for each line item.

Importantly, when both volume and price data are available, the model prioritizes the volume-based method, as it allows for more accurate environmental impact estimation by linking physical quantities to representative life cycle inventory processes. The price-based approach is only employed when physical data are missing or incomplete, serving as a fallback mechanism to ensure continuity in quantification.

This architecture ensures that climate impacts can be consistently estimated, even in the absence of detailed technical specifications, while promoting the use of the most accurate method available. Furthermore, it supports the scalable and transparent application of carbon accounting across diverse construction projects and supply chains, maintaining a clear methodological distinction between high-resolution (physical) and approximate (monetary) impact calculations. This dual capability is particularly valuable for Scope 3 emissions estimation and supplier-level benchmarking during early-stage procurement planning or supplier selection.

VII.5.4 Practical Interface for Model Deployment

To operationalize the integration described in Section 4.B.VI.5.1 (Price-Based Model), a Streamlit web application could be developed to serve as a user-friendly interface for the automation framework. This tool simplifies the deployment of both price-based and volume-based estimation models by guiding users through the key preprocessing steps required for accurate emissions calculations.

As shown in Figure 4-22, the interface allows users to:

- Upload key input files: Expenses file (Contains material line items, suppliers, and associated costs); SIREN_NAF file (Maps supplier SIREN codes to NAF codes).

N.B. The NAF-to-EXIOBASE mapping with CO_2 factors is preloaded in the app and does not require user input.

- Automatically match suppliers to their SIREN and NAF codes, and flag missing classifications where either code is absent.
- Run the full calculation pipeline, generating structured outputs including: Completed SIREN, NAF, and emission factor columns; Line-by-line traceability from raw inputs to computed outputs, with emissions calculated as: Expenses × Emission Factor (CO2eq/€) (see Figure 3-23).

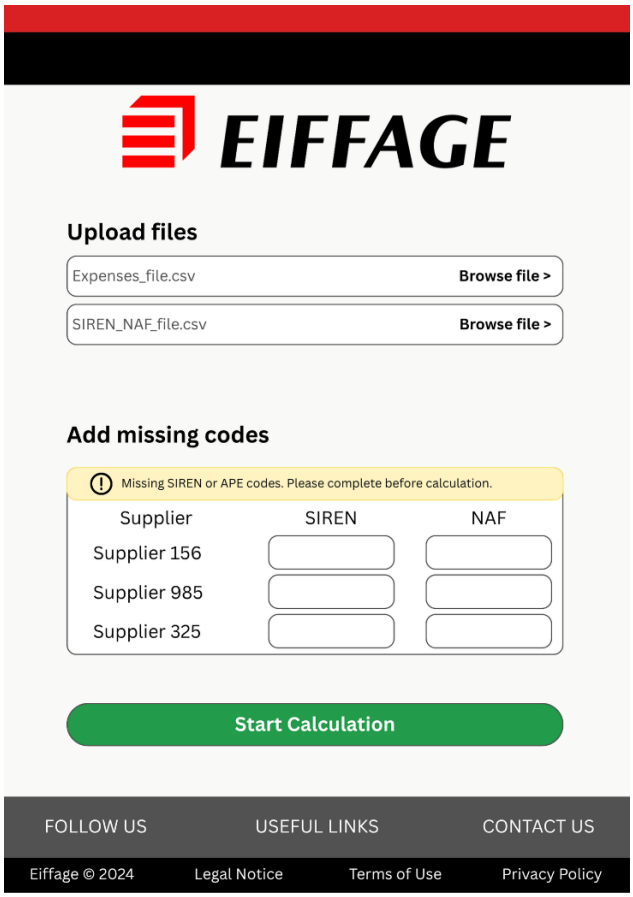


Figure 4-22 Streamlit Web Application Interface for Emission Estimation- Price-Based Model

This interface simplifies a previously manual process based on Excel lookups and code matching. It standardizes how sector mappings and emissions factors are handled, as illustrated in Figure 4.23, which shows the overall input/output structure of the model.

By embedding this into a user-friendly web interface, the system becomes accessible to non-technical users, while maintaining traceability and methodological consistency.

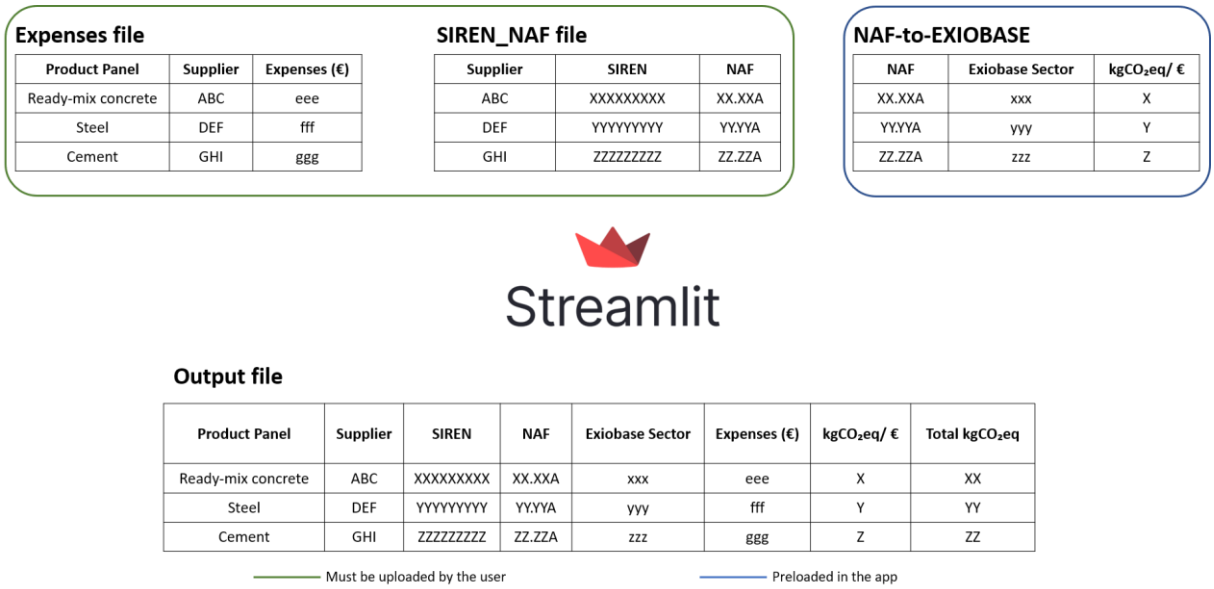


Figure 4-23 Overview of Inputs and Outputs in the Streamlit-Based Emissions Model

VI.6 Interpreting Supplier-Specific Emission Factors: Statistical Comparability and Practical Challenges

The comparative distribution of CO_2 emission factors for Suppliers 3 and 4 (Figure 4-24) provides a visual representation of variability in reported environmental performance and its divergence from standard benchmarks, including Ecoinvent 3.9.1 and internal Eiffage references. Supplier-specific data points are plotted alongside standardized values used by Eiffage divisions, revealing notable differences in central tendency and dispersion across suppliers.

Supplier 3 exhibits a relatively tight distribution centered around ~190–210 kg CO_2eq/m³, closely aligned with Ecoinvent's benchmark (~200 kg CO_2eq/m³), suggesting some internal consistency in emission reporting. In contrast, Supplier 4 demonstrates a bimodal and more dispersed profile, with values ranging from below 100 to above 300 kg CO_2eq/m³. This inconsistency suggests either genuine operational heterogeneity or methodological discrepancies in data reporting.

However, one critical issue emerges in this context: the baseline used by Eiffage to set decarbonization targets appears to be conservatively high. Benchmarks such as those used for Eiffage Construction or Infrastructure divisions consistently exceed the median of actual supplier data. This overestimated baseline can lead to distorted decarbonization planning by inflating the perceived progress of emission reductions, potentially masking the real effort needed to reach carbon neutrality. It also risks misaligning incentive structures or performance indicators with real-world supplier capabilities.

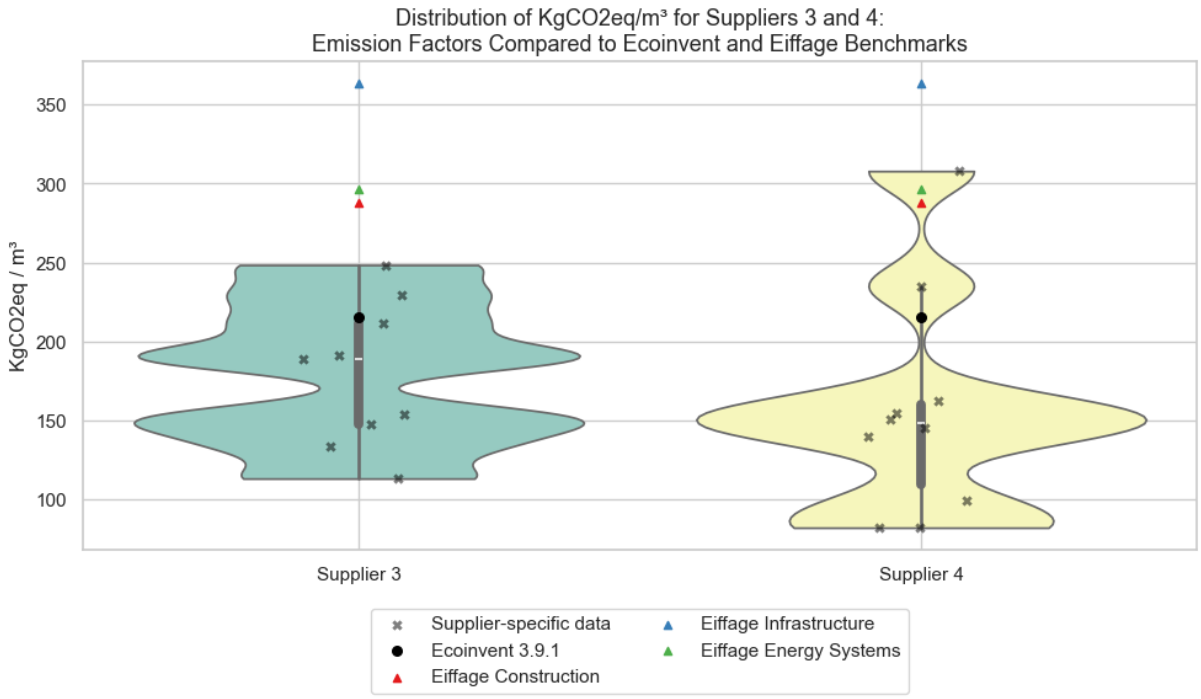


Figure 4-24 GHG Emission Factors for Suppliers 3 and 4 Compared to Reference Benchmarks

Although this comparison provides initial insight into potential supplier-level differences, it raises significant concerns about statistical comparability and data harmonization. Several systemic issues undermine the interpretability and fairness of cross-supplier comparisons:

- **Lack of scope standardization**: Some suppliers report prices as TTC (with tax), others as HT (without tax), often without clarification, creating uncertainty in monetary emissions estimates. Similarly, transport emissions are inconsistently handled, with varying assumptions on distance or inclusion, underscoring the need for standardized reporting practices.
- **Incomplete data disclosure**: Few suppliers provide all necessary variables (i.e., unit price, physical volume, CO_2 emissions, and the full calculation breakdown), complicating the direct application of the bottom-up model and obscuring emission attribution logic.
- **Imprecise volume-price-conversion ratios**: Emission intensity normalization (e.g., CO_2eq/m^3) becomes error-prone when prices are detached from clearly defined volumes or when unit conversions rely on assumptions.

In this context, Eiffage's benchmark values, while helpful for internal coherence and screening, tend to be conservative and likely overestimated. These values, derived from general averages or legacy assumptions, do not fully capture real supplier performance, especially in geographically dispersed projects with heterogeneous supply chains. As such, they may inadvertently mask supplier-level efficiency or distort comparative evaluation.

Therefore, while visual tools like violin plots offer compelling illustrations of variability, their interpretive strength is limited by input inconsistencies. This underscores the pressing need for suppliers to provide standardized, transparent, and complete data, including price, quantity, emission factors, and underlying calculation logic, with clearly defined reporting boundaries.

Going forward, organizations like Eiffage should consider requiring digital product declarations or standardized templates (e.g., aligned with PEF or EPD frameworks) to ensure reliable supplier data integration. Additionally, assigning quality scores or confidence ratings to emission data could support more nuanced interpretation and risk-aware procurement decisions. Until such standardization is achieved, the hybrid model must rely on proxy-based adjustments and careful documentation to manage uncertainty and avoid misleading comparisons.

C. Discussion

This section reflects on the methodological, practical, and strategic implications of implementing a hybrid environmental accounting framework for procurement, with a focus on its application in an industrial case study involving Eiffage. Drawing on the preceding methodological exposition and empirical demonstrations, the discussion addresses key innovations, comparative strengths and limitations across modeling tiers, data challenges, and the broader implications for Scope 3 accounting, procurement strategy, and climate management.

I. Methodological Contributions of the Hybrid Framework

The proposed model constitutes a methodological advancement in Scope 3 environmental accounting by integrating monetary and physical data in a tiered and automated structure. It leverages the flexibility and comprehensiveness of a top-down EEIO approach, while embedding bottom-up specificity through life cycle inventory LCI data and supplier-provided environmental declarations at product-level (Nakamura, 2023; Sonnemann and Margni, 2015). The use of a Systematic Tiered Hybrid Life Cycle Assessment (STHL) framework represents a departure from more rigid or ad hoc hybridization practices observed in the literature (Crawford et al., 2018; Hagenaars et al., 2025). In contrast to integrated hybrid approaches that require complete mathematical transformation of IO matrices, this tiered design supports pragmatic implementation by layering process-specific detail over a fixed EEIO structure, minimizing truncation error while preserving computational feasibility.

A further methodological novelty lies in the deployment of natural language processing (NLP) techniques, specifically, semantic embedding and transformer-based similarity models, for the alignment of French economic and product classification systems (NAF and CPF) with international environmental databases such as EXIOBASE. This allowed for a robust and scalable mapping procedure that preserved both semantic fidelity and operational relevance. While these innovations enhance classification accuracy and automation, they also introduce fragility where classification labels are ambiguous, overly generic, or poorly defined (Blanchy et al., 2023; Reimers and Gurevych, 2019; Schöpper and Kersten, 2021).

Finally, the use of an inflation-adjusted, consumption-based modeling framework grounded in pymrio and Impact World+ reinforces the alignment of this model with international standards such as the GHG Protocol and ISO 14069. The methodological rigor embedded in normalization, currency deflation, and midpoint impact characterization supports replicability and longitudinal comparability across organizations and reporting periods (© Carbon+Alt+Delete, 2025; Lawson, 2024; Leiminger, 2021). In addition, the integration of supplier-specific environmental data can be interpreted as a form of Matrix Augmentation (MA), whereby selected entries in the calculation matrix are refined or

overwritten with high-resolution, supplier-specific information. This hybridization strategy strengthens the empirical grounding of the model while maintaining structural coherence with top-down accounting logic. This approach aligns closely with OLCA principles, as it enhances organizational-level assessments by improving data granularity and representativeness at key procurement hotspots.

II. Comparative Analysis Across Modeling Tiers

A central strength of the hybrid model is its ability to dynamically allocate data sources depending on data availability and resolution. The top-down model offers broad coverage and scalability but is limited by sectoral homogeneity assumptions and aggregation biases. The product-level approach improves resolution but remains constrained by the absence of standardized CPF classifications in most procurement systems. The supplier-level model yields the highest accuracy, particularly for material-intensive or heterogeneous items, but entails significant data requirements and manual intervention (Diebel et al., 2024; Oliveira et al., 2022).

The comparison across these models underscores the value of hybridization: no single method suffices for comprehensive and accurate Scope 3 accounting. Rather, the integration of top-down monetary proxies with bottom-up physical intensities enables organizations to balance breadth and depth, applying the appropriate tier based on data maturity, product complexity, and strategic relevance (King et al., 2010; Nicholls et al., 2015).

Notably, the bottom-up model produced materially different results from monetary models in several high-impact categories (Assuncao, 2023). This divergence reflects the inadequacy of monetary proxies in capturing real-world environmental variability, especially where price signals fail to correlate with physical characteristics or environmental burdens. Conversely, for standardized products such as electricity, all three models converged, indicating that top-down approaches may suffice for commodity procurement categories with low variation.

III. Data Quality, Classification, and Semantic Matching Challenges

Despite its strengths, the model's effectiveness is highly contingent on data quality and classification consistency. The semantic mapping of NAF and CPF codes to EXIOBASE categories, although partially automated, was limited by vagueness in procurement descriptions and inconsistency in internal coding systems (Ayadi et al., 2020). Particularly in bottom-up modeling, many procurement records lacked sufficient material specification or unit data, requiring manual classification and matching.

The limitations of semantic similarity algorithms were especially evident in the bottom-up tier, where embedding models struggled to align vague or compound CPF descriptions with highly specific LCI process names. This problem was compounded by the lack of unit-awareness in existing NLP models and the complex naming conventions used in LCI datasets (e.g., "market for, at plant, CH"). These issues

reaffirm that manual verification and domain expertise remain indispensable in high-stakes categories (Lee, 2025).

Moreover, the absence of structured environmental metadata in ERP systems, such as physical quantities, CPF tags, or material composition, significantly constrained automation (Anaya and Qutaishat, 2022; El Haouat et al., 2023). The integration of environmental dimensions into procurement infrastructure remains a precondition for scaling bottom-up modeling and for achieving real-time, decision-grade environmental analytics (Alzahmi et al., 2025).

Additionally, we acknowledge that combining data from heterogeneous sources, such as supplier declarations, LCI databases, and EEIO tables, can introduce inconsistencies or amplify uncertainty, particularly when data quality or system boundaries differ (Finogenova et al., 2019; Toniolo et al., 2023). In some cases, the alignment of disparate sources may obscure rather than clarify environmental impacts. To address this, future work has to include scenario-based modeling and statistical sensitivity analysis, allowing for a more explicit treatment of uncertainty and a better understanding of how data variability affects overall footprint results and procurement decisions.

IV. Insights from the Eiffage Case

The application of the hybrid model to procurement data from Eiffage served as both a methodological test and a proof of concept. By deploying the Systematic Tiered Hybrid LCA framework across real purchasing data, this case study provided insights into the practical challenges and benefits of hybrid environmental accounting in an operational setting. A curated dataset, including over 30,000 procurement records across multiple subsidiaries, was used to implement the model's analytical tiers: supplier-level using specific declarations, bottom-up using LCI datasets, and top-down EEIO estimation. These tiers were activated sequentially based on data availability and were cross-compared to test internal consistency and identify added value at each resolution level.

The supplier-level tier proved particularly useful in identifying emissions variability across seemingly similar inputs. For instance, CO_2 intensities for ready-mix concrete varied by more than 20% between suppliers, for the same mix formula. This differentiation capability, enabled by the inclusion of supplier-specific declarations and structured formula parsing, demonstrated the diagnostic power of hybridization when granular data is available (Diebel et al., 2024; Vörösmarty and Dobos, 2020). It also validated the use of supplier-specific data as a form of matrix augmentation, where selected emission factors within the EEIO framework are empirically overwritten to reflect actual supply chain behavior.

In contrast, the product-level tier leveraged technical parsing of unstructured mix formulas to estimate emissions using harmonized and sectoral LCI data. This tier allowed for precise modeling of environmental intensities based on parameters such as cement type, exposure class, and maximum

aggregate size. The integration of NLP-based parsing and harmonization tools (e.g., for mapping cement type "CEM II/A" or chloride content "CL0,4") enabled the transformation of highly inconsistent supplier descriptions into model-ready formats (Ayadi et al., 2020; Lee, 2025). These structured attributes significantly improved the allocation accuracy of environmental impacts and allowed for meaningful filtering, benchmarking, and emissions hotspot detection within procurement categories.

Despite these strengths, the case also highlighted critical limitations, particularly in the availability of multi-indicator data. While the model architecture supports broader life cycle indicators, such as water scarcity, resource use, and land occupation, only carbon footprint (CO_2eq) data could be reliably modeled for the Eiffage dataset. Water-related data, in particular, was absent from supplier declarations and standard LCI mappings. As a result, the application remained monocriteria, focused exclusively on climate change impacts. This restricts the model's capacity to address potential trade-offs in material substitution, especially in regions affected by water stress or biodiversity concerns.

From an operational standpoint, the case study demonstrated that the hybrid model can be embedded into existing procurement workflows with manageable effort. Semantic mapping of classification codes (CPF/NAF), automated tier assignment, and structured data parsing all contributed to a more robust and transparent emissions accounting process. However, the results also underscored the need for structural improvements, including better standardization of supplier metadata, more consistent environmental disclosures, and clearer reporting boundaries.

In sum, the Eiffage case confirmed the feasibility and added value of the tiered hybrid approach, while also revealing the practical constraints that hinder more holistic life cycle assessment in procurement. The incorporation of supplier-specific data as matrix augmentation proved effective in increasing accuracy and supplier comparability. Yet, the absence of broader impact indicators calls for enhanced supplier engagement, standardized digital documentation, and investment in traceable, machine-readable data streams. As such infrastructure matures, the proposed hybrid model stands as a scalable and adaptive solution for next-generation procurement-based environmental accounting.

V. Limitations and Recommendations for Future Development

Table 4-13 presents a structured summary of the key limitations encountered during the operational implementation of the hybrid environmental accounting framework within Eiffage's procurement system. Each limitation is directly linked to a targeted recommendation, providing clear pathways for methodological refinement, data integration, and system-level improvements. This correlation supports actionable development planning and offers a roadmap for scaling the hybrid model toward more accurate, transparent, and decision-relevant Scope 3 emissions accounting.

Table 4-13 Summary of Identified Limitations and Corresponding Recommendations for Future Development

Limitation	**Description**	**Recommendation**
Over-Reliance on Outdated Monetary Emission Factors	LODACE relies on emission factors from 2002 USD, later converted to 2024 EUR. This 20+ year gap leads to inaccurate estimates due to inflation, outdated sector data, and inconsistent currency conversion.	Adopt up-to-date, sector-specific emission factors (e.g., EXIOBASE v3.8 in 2024 EUR) and apply region-specific adjustments to reflect current economic and environmental realities.
Absence of Supplier-Specific Emissions Integration	All suppliers within a material category are treated as environmentally equivalent, overlooking significant differences in production methods, cement types, and carbon footprints.	Integrate supplier-specific emission factors into LODACE to enable differentiated carbon tracking. Link these to procurement records at the BU, DR, and BR levels to support low-carbon sourcing decisions.
Inconsistency and Fragmentation in Supplier Data	Supplier-provided datasets vary in format, completeness, and nomenclature, making aggregation and comparison difficult, and requiring intensive manual intervention.	Develop standardized supplier data templates aligned with NF EN 206-1 and EPD conventions. These should include clear fields for mix designation, CO_2 emissions, volumes, and prices, with optional fields for transport and binder content.
Manual and Non-Automated Preprocessing of Mix Formulas	The transformation of unstructured concrete mix formulas into model-ready data is currently manual, impeding scalability and increasing error risk.	Automate the preprocessing workflow using Python scripts or APIs, embedding it directly into procurement platforms. Include regex filters and a dynamic terminology dictionary for supplier-specific codes.
Inconsistent Inclusion of Transport and Tax in Emission and Price Data	Suppliers differ in whether emissions and prices include transport or VAT, affecting comparability across suppliers and misrepresenting environmental performance.	Implement a supplier disclosure protocol requiring explicit clarification of system boundaries (e.g., plant gate vs. delivered site) and financial conditions (HT vs. TTC). Apply normalization rules to harmonize incoming data.
Limited Physical Refinement Across Material Categories	Physical LCI-based refinements are applied only to concrete-related materials, leaving other procurement categories (e.g., steel, bitumen, equipment) reliant on generalized monetary proxies with ±50% uncertainty.	Expand physical modeling and refinement using LCI databases (e.g., ecoinvent, Base Empreinte® ADEME) to other high-impact procurement categories. Prioritize sectors with high carbon intensity and supplier engagement potential.

Limitation	Description	Recommendation
Absence of Carbon-Performance Feedback Loops	LODACE does not retain emissions history or use past procurement-emission matches to inform new purchases. This limits predictive accuracy when technical specifications are absent.	Implement a feedback mechanism that stores previously modeled configurations with unit prices and emission intensities. When only price data is available, use this historical logic to infer probable mix characteristics and emissions.
Underutilized Regional Price Variability	Same mix configurations are priced differently across Eiffage's divisions, but this variability is not systematically analyzed for carbon or cost optimization.	Leverage regional weighted-average pricing data to identify procurement efficiency opportunities. Use this to support region-specific procurement strategies that optimize for both cost and carbon intensity.
Limited Cross-Sector and Cross-Material Applicability	The framework has been tested primarily on concrete, limiting insights for other product families such as steel, machinery, or services.	Pilot the hybrid model in adjacent material families using sector-specific EPDs, LCI datasets, or digital product passports. Assess generalizability and refine decision logic accordingly.
Supplier Engagement Remains Informal and Voluntary	Supplier data is currently provided on a best-effort basis. No formal requirement or verification process exists to ensure data quality or completeness.	Institutionalize supplier engagement via annual reporting protocols, integrated into contract terms. Consider requiring EPDs or third-party verified carbon declarations for key material categories
Limited Strategic Use of Scope 3 Accounting	Scope 3 procurement accounting is still treated as a static, compliance-driven task rather than a dynamic management tool.	Transform Scope 3 accounting into a scalable, decision-support system by leveraging the hybrid framework's multi-tier logic, enabling data-driven supplier evaluation, emissions tracking, and integration into strategic procurement and sustainability planning.
Underutilized Regional Price Variability	Same mix configurations are priced differently across Eiffage's divisions, but this variability is not systematically analyzed for carbon or cost optimization.	Leverage regional weighted-average pricing data to identify procurement efficiency opportunities. Use this to support region-specific procurement strategies that optimize for both cost and carbon intensity.

VI. Enhancing the Model through Cost Accounting Integration and Multidimensional Impact Assessment

While the hybrid model presented in this chapter effectively combines environmental data from both monetary and physical sources, its real-world application remains constrained by fragmented procurement information and the lack of structured, verifiable inputs from suppliers. A core challenge is not just the collection of emissions data, but also the consistent availability of volume and price data, which are essential for robust and scalable sustainability accounting (Marx et al., 2020; Pedersen and Remmen, 2022; Stridsland et al., 2023b).

To address these limitations, future developments could integrate cost accounting systems, particularly Activity-Based Costing (ABC). ABC models enable the tracing of both direct and indirect costs to specific activities and resource flows, serving as useful proxies for physical quantities (Cooper and Kaplan, 1988; Kaplan and Anderson, 2007). This linkage supports a bottom-up estimation of environmental impacts, especially in contexts where detailed technical data are scarce but financial structures are well-defined.

As demonstrated by Jourdaine et al. (2021), coupling ABC with LCA improves the granularity and relevance of impact assessments by aligning environmental performance with economic activity. Yet, sustainability is not limited to carbon emissions. A truly holistic framework must also account for social and other environmental indicators. By expanding hybrid accounting models to include these dimensions, particularly through the integration of Social Life Cycle Assessment (S-LCA), organizations can move toward multi-criteria sustainability evaluation in procurement.

The next chapter explores this direction further, proposing two distinct but complementary extensions:

1. An evolution of the top-down hybrid model to incorporate social indicators, offering a pathway for embedding social dimensions into existing monetary-based sustainability assessments.
2. A refinement of the ABC-LCA model introduced by Jourdaine et al., suggesting how activity-based structures can be expanded to support integrated social accounting.

These conceptual extensions are not yet reflected in current procurement practices but serve as a forward-looking attempt to align sustainability frameworks with real-world constraints, supporting the development of more inclusive, transparent, and responsible procurement strategies.

5| Advancing Social Integration in Procurement Sustainability Accounting

While environmental accounting, especially for carbon, has become more sophisticated in recent years, the integration of social impacts into procurement-related assessments remains limited. This chapter explores how sustainability accounting frameworks can evolve to incorporate social dimensions, ensuring that corporate responsibility extends beyond emissions.

***Section A** proposes a conceptual expansion of the existing top-down monetary model to include social indicators, offering a pathway for embedding social criteria into high-level, expenditure-based assessments.*

***Section B** refines the Activity-Based Costing (ABC)–Life Cycle Assessment (LCA) model introduced by Jourdaine et al. (2021), showing how cost structures and operational data can be used to support socially integrated, activity-based accounting.*

Together, these three approaches offer complementary strategies for building a more inclusive, multidimensional model of sustainability in procurement.

A. Expanding the Top-Down Monetary Model to Integrate Social Indicators

This section expands the existing top-down environmental modeling framework to incorporate social sustainability dimensions, drawing on the integration logic developed in earlier chapters. It introduces a methodological enhancement that links procurement expenditures to social impact indicators, using sector-based risk intensities derived from the PSILCA database. Building on the monetary alignment and classification structure established previously, the model translates qualitative social risks, such as corruption and gender inequality, into quantifiable metrics, enabling dual-impact accounting. This extension provides a structured basis for evaluating social risks across procurement flows, aligning with emerging reporting standards and supporting organizations in their transition toward more comprehensive sustainability assessment.

This section contributes to an article by Essouid et al., "Integrating Social and Environmental Intensities into Procurement-Based LCSA: A Sector-Level Framework for France", which is currently under finalization.

I. Introduction

While the top-down model has proven effective for attributing environmental impacts to procurement expenditures, particularly when physical product-level data is unavailable, its current formulation does not address the social dimension of sustainability. Kronenberg (2010) underscores the observation that input-output models, though extensively used for environmental and economic impact analysis, have historically neglected the social dimension of sustainability. This section proposes a conceptual expansion of the model to incorporate social indicators, creating a dual-impact framework that accounts for both environmental and social externalities at the sector level.

The proposed extension builds upon the monetary alignment architecture established in Section 4.A, leveraging the same codification systems (e.g., NAF, SIREN) and economic classification logic (e.g., EXIOBASE sectors). However, rather than assigning environmental intensities (e.g., kg CO_2/€) alone, the enhanced model seeks to allocate social performance scores or risks per euro spent, based on sector-adjusted indicators relevant to labor conditions, human rights risks, or social equity.

Among the various S-LCA databases reviewed in Chapter 2, PSILCA was selected as the preferred data source for this top-down integration due to its structural compatibility with monetized input-output modeling and its extensive sectoral and geographic coverage. Unlike SOCA, which is designed for process-specific, bottom-up analyses based on physical reference flows, PSILCA models social risks using a hybrid approach that combines worker-hour allocation with monetized economic flows (USD),

making it uniquely suited for integration with expenditure-based procurement data (Hamed and Ciroth, 2024; Maister et al., 2020). PSILCA's modeling approach, structural compatibility with input-output frameworks, and wide sectoral/country coverage have been highlighted in several recent peer-reviewed studies as strengths for monetary-sector social LCA (Costa et al., 2022; Kronenberg, 2010; Tragnone et al., 2023). Furthermore, its underlying structure aligns with the MRIO logic of EXIOBASE, enabling consistent linkage between financial transactions and sector-level social indicators. PSILCA also offers a broader coverage of processes, countries, and social themes than SHDB, enhancing its utility for comprehensive, cross-sectoral assessments of social risk (Benoit-Norris et al., 2018; Maister et al., 2020). Its dual modeling system allows for flexible use of either direct data or labor activity proxies, depending on indicator availability, thereby supporting a nuanced yet scalable implementation of social impact accounting in monetary terms.

(Sairinen et al., 2021)While analyzing the database structure, an observation is that the original structure of PSILCA is not directly compatible with the proposed top-down modeling. Its organization of processes, use of an outdated monetary unit, and limited sectoral alignment with regional classification systems present practical barriers to integration. These limitations underscore the need for a dedicated and automated transformation pipeline to restructure and harmonize the data before it can be used effectively in an expenditure-based context.

II. Materials and Methods

II.1 Operationalization and Transformation of PSILCA Data for Top-Down Integration

While the PSILCA v3.0 database offers rich sectoral and regional social risk coverage, its native structure and unit of measurement (h/USD2011) are not directly compatible with the proposed top-down monetary modeling frameworks that operate on French classification systems such as NAF and financial reference units like EUR2024. To enable meaningful integration into a procurement-based model aligned with the logic of EXIOBASE and hybrid LCA workflows, a Python-based data transformation pipeline was developed to restructure, standardize, and weight the social indicators from PSILCA. The code-based pipeline performs a series of structured operations to adapt PSILCA data for integration into a monetary top-down modeling framework. The core transformation steps are outlined below (Figure 5-1):

- *Parsing PSILCA Process Blocks* : The raw PSILCA export is structured as a semi-tabular file, where each process begins with the line “Process” and ends with “End”. The script identifies these blocks using string-matching logic and extracts metadata including the "Process name" and the section labeled "Social issues". This structure reflects PSILCA's model of allocating social risk indicators of 1 USD output across sectors and countries, such as “Industries – Agriculture – AFG”.

- *Extraction of Social Indicators and Qualitative Risk Levels* : For each process, the script captures all social indicators listed under the "Social issues" section along with their associated qualitative risk level and activity variable. These indicators are stored with the following fields: Process name; Social issue; Risk level (e.g., very high risk, low opportunity); Value (activity variable, in h/USD2011). Each social indicator label is split into two parts: the issue name and the risk level, which is parsed automatically when it follows a " - " delimiter.
- *Risk Level Characterization* : Following PSILCA's official guidelines (Maister et al., 2020), qualitative risk and opportunity levels were mapped to quantitative risk factors using a predefined dictionary: Very low risk, 0.01; Low risk, 0.1; Medium risk, 1; High risk, 10; Very high risk, 100; No risk/opportunity, 0; Low opportunity, 0.1; Medium opportunity, 1; High opportunity, 10; No data, 0.1. These mappings are implemented via Python logic that handles case variation and string formatting errors to ensure robustness. Rows without recognized levels are excluded.
- *Computation of Weighted Risk Values* : Once risk levels were numerically characterized, the script (Equation 5-1) computed a weighted social impact value per process and indicator by multiplying the activity variable "worker hours", defined as the number of working hours per unit of economic output (e.g., 5h/USD2011) (Springer et al., 2025), by its corresponding risk factor:

$$\boldsymbol{Weighted\,Value} = \boldsymbol{Risk\,Factor} \times \boldsymbol{Activity\,Variable}$$

Equation 5-1 Computation of Weighted Risk Values

This transformation yields a normalized metric of social impact, expressed in medium risk hours (mrh). The metric integrates both the quantity of labor (via the activity variable) and the severity of the associated social issue (via the risk factor). For example, an indicator with an activity variable of 5 h/USD and a risk level classified as high risk (risk factor = 10) results in a weighted impact of 50 mrh/USD. At this stage, the activity variable remained in its native unit (mrh/USD2011).

- *Reformatting for Model Integration* : The final data structure is prepared in both long and wide formats: The long format lists each process with its social issues and weighted values (Table 5-1):

Table 5-1 Data Structuring Formats: Long Representations of (Direct) Social Risk Indicators

Process name	Social issue	Risk level	Value (h/USD2011)	Weighted value
Industries - Manufacture of textiles - FRA	Gender wage gap	medium risk	0.006450127	0.006450127
Industries - Manufacture of textiles - FRA	Health expenditure, total	low risk	0.006450127	0.000645013
Industries - Research and development - FRA	Gender wage gap	medium risk	0.009571122	0.009571122
Industries - Research and development - FRA	Health expenditure, total	low risk	0.009571122	0.000957112

The wide format is generated via a pivot table, with one row per process and one column per social issue (Table 5-2). Each cell contains the weighted value, facilitating integration with LCA or Scope 3 tools.

Table 5-2 Data Structuring Formats: Wide Representations of (Direct) Social Risk Indicators

Process | Social issue	Gender wage gap	International Migrant Stock	Health expenditure, total
Industries - Manufacture of textiles - FRA	0.006450127	0.064501269	0.000645013
Industries - Research and development - FRA	0.009571122	0.095711215	0.000957112

Although both formats were generated, the wide-format dataset was primarily used in the subsequent modeling steps due to its compatibility with top-down monetary models and ease of integration with environmental impact matrices.

Once structured in the wide format, these weighted values represent direct social intensities, that is, the expected social risk per unit of economic output (e.g., in h/USD2011) within the sector producing the good or service. Indirect impacts, by contrast, reflect the contribution of upstream sectors. These are computed by multiplying the value of monetary inputs from each sector by that sector's own social risk intensity. The sum of direct and indirect impacts yields the total social footprint, enabling a full-chain perspective consistent with environmental input-output modeling and Scope 3 accounting logic.

- *Currency and Inflation Adjustment* : A monetary normalization to EUR2024 was planned for later stages, which would apply a two-step adjustment:
  - Inflation correction (USD2011 → USD2024): ≈ ×1.3885 (U.S. Bureau of Labor Statistics, 2024)
  - Currency conversion (USD2024 → EUR2024): ≈ ×0.93 (European Central Bank, 2023)

This would yield: 1 USD2011 ≈ 1.2913 EUR2024.

This factor is then applied to the weighted values, effectively converting social impact units from mrh/USD2011 to mrh/EUR2024. This adjustment is crucial for achieving internal consistency between PSILCA-derived social indicators and monetary data used in environmental LCA, Scope 3 accounting, and economic modeling.

- *Geographic Filtering* : To tailor the analysis to the French industrial context, a subset of the PSILCA database was isolated, including only processes whose names begin with "Industries – [Activity] – FRA". This filtering step allowed the creation of a reduced, country-specific database centered on industrial activities located in France. This curated subset ensures alignment with national policy frameworks and reporting standards, while simplifying testing and validation of the integration logic.

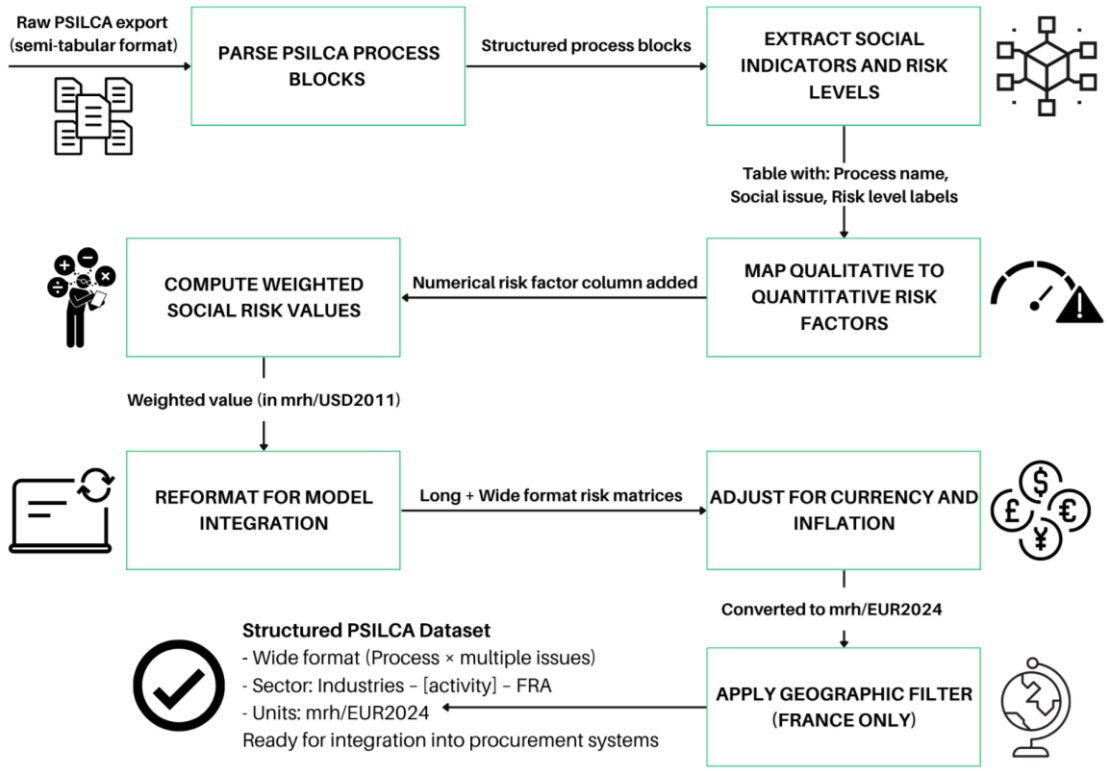


Figure 5-1 PSILCA Data Transformation Pipeline

II.2 Prototype Development and Data Integration Using PSILCA v3.0

This implementation should be regarded as a proof-of-concept prototype, developed using version 3.0 of the PSILCA database, which, although not the most recent release, was the latest version available within the research laboratory at the time of this study. While PSILCA v3.0 provides a robust modeling architecture and extensive global coverage of social indicators, it presents several limitations that constrain its immediate applicability in current European policy and economic contexts (Sala et al., 2015). Notably, all activity variables are expressed in constant U.S. dollars from 2011 (USD2011), requiring monetary normalization to reflect present-day values (Macombe et al., 2013). More recent versions of the database, including PSILCA v4.0, are expected to offer several enhancements, such as updated economic reference years (e.g., USD2019), improved geographic and sectoral resolution, and expanded sets of social themes and indicators. The transformation pipeline developed in this work has been intentionally designed to be modular and adaptable; as such, it can accommodate newer PSILCA releases with minimal modification. Risk characterization and unit conversion are parameterized, allowing for rapid reprocessing of updated datasets and enabling continuous integration of improved data sources into top-down social impact modeling workflows.

II.3 Integration of Social Indicators into the Monetary-Based Top-Down Model

Building upon the database structure developed in Section I, this section demonstrates how social risk indicators derived from the PSILCA database can be integrated into the same monetary modeling

framework used for environmental impacts. As outlined in Section 4.A.I, the top-down model leverages financial expenditure data (e.g., procurement records) and maps it to economic sectors via national classification codes (NAF), which are semantically aligned with EXIOBASE sector intensities. The present extension introduces a parallel mapping approach that applies social indicators to the same set of sectors and transactions.

The objective of this section is to explore the feasibility of dual sustainability accounting, i.e., tracking both environmental and social externalities, within a unified, procurement-driven framework. Specifically, the model is extended by incorporating social risk intensities, measured in medium risk hours per euro (mrh/EUR2024), derived from the weighted values computed previously. These values result from transforming PSILCA's qualitative risk levels and activity variables into normalized quantitative scores using a risk factor weighting system. While this approach allows for integration and comparability, it is important to note that the results are inherently shaped by the underlying weighting methods employed in PSILCA. These methods, though systematically designed, carry certain limitations regarding transparency, subjectivity in expert-based scoring, and sensitivity to assumptions. Consequently, all findings must be interpreted with an awareness of the strengths and constraints of PSILCA's weighting approach.

To maintain analytical clarity and ensure focus, this section restricts the analysis to two key social indicators that are broadly relevant across industries and frequently cited in international reports (UN, 2004; UNECE, 2011):

- Active Involvement of Enterprises in Corruption and Bribery (AI): This indicator reflects the estimated likelihood of enterprises engaging in corrupt practices, such as bribery, fraud, or embezzlement, within a given sector or region. It serves as a proxy for governance integrity and legal compliance, with higher values indicating increased exposure to institutional and reputational risks, often in contexts of weak regulatory enforcement.
- Gender Wage Gap (GW): This indicator refers to the difference in average earnings between men and women for comparable work. It is typically expressed as a percentage of male earnings and is a widely used indicator of gender-based inequality in the labor market.

These indicators were selected for their interpretability, data availability, and policy relevance, particularly in the context of European regulations and CSR frameworks.

Notably, both indicators are directly referenced in the CSRD (European Commission, 2023a) under the ESRS S1 and G2 standard , which mandates disclosure of G2-6-Corruption or bribery events and S1-16-Pay gap between women and men, for the reporting company, under the performance measurement section. While these disclosures are currently limited to direct employees, future regulatory

developments and stakeholder expectations are expected to expand the scope toward supply chain coverage. The integration of such indicators at the supplier level, as demonstrated here, thus anticipates upcoming compliance needs and supports the development of scalable social due diligence frameworks.

Their inclusion in this model serves not only as a proof-of-concept for extending social footprinting in top-down models but also as a preparatory step for integrating mandatory reporting obligations and value chain transparency into sustainability accounting workflows.

From a methodological standpoint, the same modeling steps used in Section 4.A.I are applied here. However, instead of multiplying monetary values by environmental intensities (e.g., kg CO_2/ EUR2024), we apply social intensities derived from PSILCA (e.g., mrh/EUR2024). These intensities, which reflect the risk-adjusted labor impact per unit of economic output, are sector-specific and maintain full compatibility with the EXIOBASE classification logic and the monetary structure of procurement data.

The computational workflow remains identical (see Figure 4-1), procurement transactions are matched to NAF codes, mapped to sectoral categories, and then multiplied by their respective intensity coefficients. This substitution of environmental with social intensities yields a parallel social footprint matrix, enabling direct comparison between environmental and social risks across suppliers, categories, and activities.

This harmonized dataset provides a comprehensive basis for double materiality assessments, integrating both environmental and social thresholds into procurement-driven sustainability evaluations.

III. Demonstration Results

To illustrate the functionality of this extension, the same demonstration procurement dataset (Table 4-2) is used. Social impacts (in mrh) will be computed for each transaction, and visualized in Figure 5-2. This not only enhances the model's granularity but also sets the foundation for multi-dimensional sustainability accounting that integrates environmental, social, and potentially economic indicators into a single decision-support framework.

Table 5-3 presents a supplier-level assessment of social risks, combining both financial expenditures and sector-specific social intensities expressed in medium risk hours (mrh) per euro. Two indicators are analyzed: Active Involvement in Corruption and Bribery (AI) and the Gender Wage Gap (GW). By multiplying each supplier's expenditure (in EUR2024) by the corresponding sector-level risk intensity, the resulting impact values capture the scale and severity of potential social issues associated with procurement flows. Such disaggregated supplier-level results allow organizations to identify social

hotspots within their value chains and prioritize actions such as supplier engagement, due diligence, or targeted capacity-building programs.

All suppliers were successfully mapped to corresponding PSILCA sectors using their NAF codes, with full consistency across sectors when compared to EXIOBASE classifications. This is largely due to the fact that both databases are structured around the common NACE framework. The only exception was electricity generation (S9), where PSILCA groups it under a broader utility category. This high degree of alignment reinforces the robustness of the sectoral mapping process and enhances confidence in integrating environmental and social indicators within a unified model.

As shown in Figure 5-2, the bar chart visualization facilitates rapid identification of suppliers contributing disproportionately to social risks, even when financial expenditures appear moderate.

From a monetary standpoint, suppliers S3 and S7 (both in construction-related activities) stand out with the highest total expenditures, but also with the highest social intensities, reaching up to 0.8984 AI mrh/EUR and 0.0607 GW mrh/EUR. These high coefficients indicate that for each euro spent in this sector, a relatively large number of socially weighted risk hours are generated. As a result, their total social footprints are exceptionally large: S3 alone contributes over 10,700 AI mrh, despite representing only about 28% of total expenditures, confirming that both volume and intensity play critical roles in social risk accumulation.

In contrast, suppliers such as S5 (head offices) or S4 (traditional restoration) display much lower social intensities (e.g., 0.0805 AI mrh/EUR), and when combined with modest expenditures, their resulting social impacts remain relatively low — under 140 AI mrh in both cases. This highlights that some sectors are structurally less exposed to systemic social risks, regardless of their spend levels.

Table 5-3 Demonstration Output: Supplier-Level Social Impact Allocation Using Sector-Based Intensities

Supplier	SIREN	NAF	Sector	PSILCA sector	AI mrh/ EUR2024	GW mrh/ EUR2024	Expenditures (EUR2024)	AI mrh	GW mrh
S1	403683667	32.50A	Manufacture of medical, surgical and dental equipment	Manufacture of medical, precision and optical instruments, watches and clocks	0.12698	0.08613	2000	253.971	172.2664795
S2	404942344	46.69C	Wholesale trade (business-to-business trade) of miscellaneous supplies and equipment for trade and services	Wholesale trade and commission trade, except of motor vehicles and motorcycles	0.17994	0.04786	3500	629.786	167.518
S3	519764823	43.99D	Other specialized construction work	Construction	0.8984	0.0607	12000	10780.552	728.396
S4	539779272	56.10A	Traditional restoration	Hotels and restaurants	0.13807	0.05417	1000	138.067	54.175
S5	853838043	70.10Z	Activities of head offices	Other business activities	0.08054	0.0391	500	40.270	19.548
S6	791399603	46.42Z	Wholesale trade (business-to-business) of clothing and footwear	Wholesale trade and commission trade, except of motor vehicles and motorcycles	0.17994	0.04786	4850	872.704	232.132
S7	950323675	43.99A	Sealing work	Construction	0.8984	0.0607	8000	7187.035	485.597
S8	443858865	47.22Z	Retail trade services of meat and meat products in specialised stores	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	0.13123	0.03674	3980	522.314	146.228
S9	752234591	35.11Z	Electricity generation	Electricity, gas, steam and hot water supply	0.46749	0.06717	750	350.620	50.374
S10	478250418	43.32A	Wood and PVC carpentry works	Manufacture of wood and of products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials	0.15075	0.06125	6900	1040.182	422.6169
Total							**43480**	**21815.507**	**2478.856**

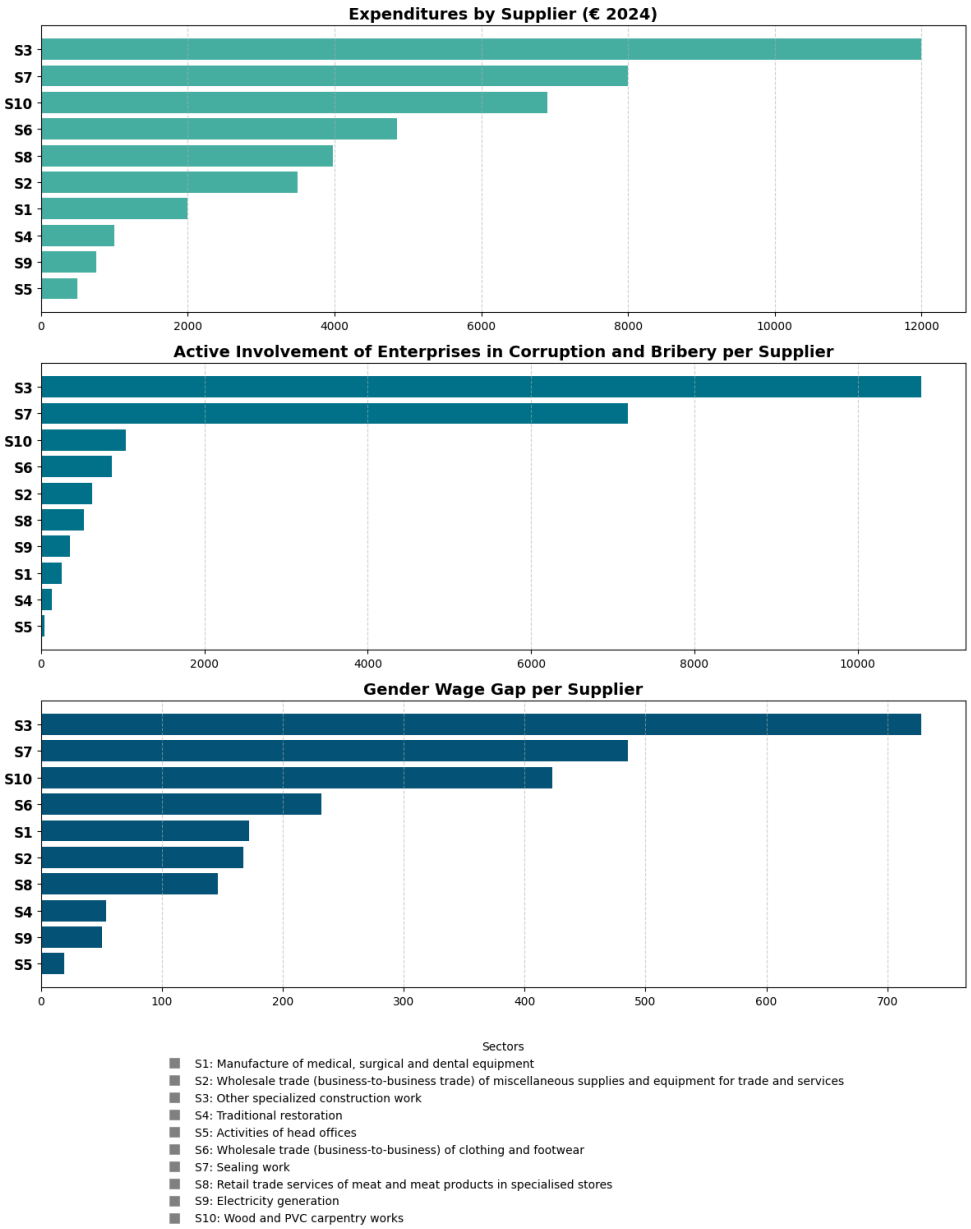


Figure 5-2 Bar Chart of Supplier-Level Social Impacts Using Sector-Based Intensities

It is important to note that while both AI and GW indicators are expressed in the same unit (mrh), their scales and sectoral distributions differ, making them complementary rather than directly comparable indicators of social risk.

Taken together, the analysis reveals that high expenditures in high-intensity sectors (like construction) lead to amplified social risks, while low-intensity sectors or low spend levels naturally produce smaller footprints. The AI indicator generated over 21,800 mrh, while GW totaled nearly 2,480 mrh, both expressed in medium risk hour equivalents per euro spent.

The reported values represent total social impacts, combining both direct effects from suppliers and indirect effects from upstream sectors supplying goods and services to those suppliers. This full-chain perspective mirrors the logic of Scope 3 assessments.

This approach can be readily scaled across larger procurement portfolios or institutional buyers using structured financial data and sector mappings.

IV. Discussion

The demonstration of social impact integration into a top-down monetary modeling framework reveals both methodological potential and practical constraints. By extending the logic used for environmental footprinting, the model enables a dual-assessment approach, quantifying both environmental and social risks per euro spent. The inclusion of indicators such as Active Involvement in Corruption and Bribery and the Gender Wage Gap illustrates how social dimensions, often overlooked in procurement analyses, can be operationalized using harmonized classification systems and sector-level intensities (Sairinen et al., 2021). The results underscore the fact that sectors with both high expenditures and high social intensities, such as construction, are responsible for the majority of the social footprint, paralleling known environmental hotspots and reinforcing the need for integrated decision-making frameworks (Kronenberg, 2010).

This integration is particularly timely in light of evolving regulatory landscapes. The Corporate CSRD, through its European Sustainability Reporting Standards (ESRS), introduces specific disclosure requirements for indicators like S1-16 (Gender Pay Gap) and G2-6 (Corruption or Bribery Events) (European Commission, 2023a). While these currently focus on the reporting entity's own workforce, they are expected to expand toward upstream supply chain coverage in future regulatory iterations (Sheen, 2023). By pre-emptively modeling supplier-level social risks, this approach provides organizations with a foundational tool for compliance, due diligence, and stakeholder engagement.

The consistency between PSILCA and EXIOBASE sector mappings, rooted in the shared NACE classification, reinforces the model's internal robustness. This compatibility also opens avenues for further extension (Maister et al., 2020). For instance, the product-by-product version of EXIOBASE could be aligned with the commodities-level variant of PSILCA, following the same transformation pipeline developed in Chapter 4. Similarly, process-based databases like ecoinvent can be coupled with social datasets such as SOCA for bottom-up integration, particularly in contexts where product-level modeling or material-specific analysis is prioritized (Hamed and Ciroth, 2024). These connections highlight the versatility of the architecture, enabling a wide range of applications from procurement-based modeling to product-specific assessments.

Despite this flexibility, limitations persist, particularly regarding data granularity. Supplier-level social data is rarely available, and company-specific risk profiles are often difficult to obtain (Ayassamy and Pellerin, 2023; Waldekker and Molnar, 2014). As such, sector-level approximations remain a necessary simplification in most applications. To mitigate this gap, integration with internal cost accounting systems, such as Activity-Based Costing (ABC) models, can provide a bridge (Jourdaine et al., 2021). By linking procurement data to operational cost centers and associated activities, ABC enables finer resolution in impact attribution. This potential coupling is explored further in Section B, where cost-based allocation structures are investigated as a mechanism for scaling social and environmental accounting throughout the enterprise.

V. Conclusion

The framework developed here provides a replicable and scalable foundation for dual-materiality assessments. It offers organizations a structured pathway to incorporate social risks into their procurement analytics and sustainability reporting workflows, even in data-limited environments. By anchoring the model in established economic classifications and regulatory priorities, it positions itself as both a technical solution and a strategic enabler of responsible sourcing.

B. Time Driven Activity-Based Costing and Social Life Cycle Assessment: An Integrated Framework

This section introduces the rationale, structure, and methodological innovation behind combining TD-ABC and S-LCA to address the limitations of traditional cost accounting in capturing social impacts. The section outlines the theoretical foundation, details the computational steps, and presents an illustrative case study in the packaging sector to demonstrate the model's operational feasibility and potential managerial relevance. Through this integration, the framework aims to enhance social accountability in corporate decision-making by linking activity-level cost data with stakeholder-specific social risk metrics.

The framework presented here is based on two forthcoming publications by Essouid et al. The first is the book chapter "De la comptabilité des coûts à la soutenabilité sociale: un modèle intégré pour les entreprises", to appear in Analyse sociale de cycle de vie: enjeux, théorie et pratiques, Paris, Presses des Mines (2026). The second is the article "Time-Driven Activity-Based Costing and Social Life Cycle Assessment: An Integrated Framework", accepted for publication in Corporate Social Responsibility and Environmental Management

I. Introduction

Amid growing calls for integrated sustainability metrics, this section introduces a novel framework that combines TD-ABC with S-LCA, offering a practical pathway to link social impact measurement with internal cost structures.

As noted by Kaplan & Ramanna (2021), environmental accounting has made significant progress in recent decades, particularly in addressing climate change and global warming. Several approaches have been proposed and applied in different sectors such as in banking, agriculture, and manufacturing. A review by Ayinla et al. (2024) demonstrates the key advancement and milestones achieved in sustainability accounting while highlighting the complexity of integrating environmental costs into traditional accounting systems.

In parallel, social accountability has evolved from early Corporate Social Responsibility (CSR) initiatives in the 1970s to include standards like SA 8000, which addresses workers-related social issues such as child labor, forced labor, and discrimination of employees (Turzo et al., 2024). Broader frameworks, such as ISO 26000 (2010), emphasize the need to assess impacts on all stakeholders (i.e., workers, local communities, consumers, and value chain actors). Despite growing pressure from shareholders and other stakeholders, existing accounting systems remain poorly equipped to capture environmental and social dimensions.

To provide a holistic view of sustainability, the Life Cycle Sustainability Assessment (LCSA) framework was introduced, combining Environmental LCA, Social LCA (S-LCA), and Life Cycle Costing (LCC) (UNEP, 2011; Valdivia and Sonnemann, 2024). However, implementing these tools in corporate contexts remains a major challenge.

Since the mid-1980s Activity-Based Costing (ABC) has helped companies address overhead allocation issues (Cooper and Kaplan, 1988). More recently, TD-ABC was developed to improve accuracy and implementation simplicity (Kaplan and Anderson, 2004). While both models offer strong internal data structures, they have largely overlooked sustainability dimensions[6]. However, some authors have noted that ABC models were close to Life Cycle Assessment (LCA) methodology, based on matrix calculations (Afonso and Paisana, 2009). This has created a new opportunity to merge these two methods.

In this context, Jourdaine et al. (2021) developed the ABC-LCA model, combining traditional ABC with environmental LCA to better align cost drivers and environmental flows. However, no existing study has yet operationalized a robust integration of social performance indicators within a TD-ABC system.

Building on the ABC-LCA methodology (Jourdaine et al., 2021), this research proposes a new approach: TD-ABC-S-LCA (Time-Driven Activity-Based Costing and Social Life Cycle Assessment). The aim is to integrate S-LCA metrics directly into the TD-ABC structure, thereby enabling a more detailed and context-sensitive understanding of social impacts associated with business operations and procurement. This model leverages time as a unit of analysis and uses cost flows for underlying social processes and stakeholder exposures.

We then test this approach through an illustrative case study in the packaging sector , chosen for its complex supply chain dynamics and relevance in sustainability-driven procurement, to demonstrate its usefulness in balancing social and economic performance in managerial decision-making and supporting real-world application. By aligning social impact assessment with familiar accounting tools, the proposed framework contributes to advancing the practical integration of sustainability in corporate practice.

[6] Although the purpose of the ABC model is to analyze the resources used, there has never been any question of their links with natural capital, and whether or not they are exhaustible or renewable (Cooper & Kaplan, 1988). There is a similar blind spot on social issues.

Our primary research questions: ***How can data structures of Time-Driven Activity-Based Costing (TD-ABC) and Social Life Cycle Assessment (S-LCA) be effectively integrated? And what managerial benefits can this integration provide?***

The article is structured as follows: Section II details the methodological framework, outlining both approaches and their integration, and applies this methodology to a case study in the packaging sector, describing the implementation process and data collection. Section III presents and analyzes the results, comparing social impacts, identifying key contributors, and assessing geographic variability. Section IV discusses the main findings, highlighting their implications for supply chain management and social accounting. Finally, section V concludes by summarizing the study's contributions and proposing directions for future research.

The present work is based on two different approaches, namely Social Life Cycle Assessment (S-LCA) and Time Driven Activity-Based Costing (TD-ABC), introduced earlier in Chapter 2.

As introduced in Chapter 2, TD-ABC improves upon traditional ABC by using estimated time equations as cost drivers, eliminating the need for detailed activity surveys (Kaplan and Anderson, 2004). It allocates costs based on the time required to perform activities, enabling more efficient cost tracking and identification of unused resource capacity, which can be reallocated to higher-value tasks. This enables decision-makers to reallocate resources to new products more effectively or optimize resources use[7].

Importantly, costs are assigned not only to products but more generally to cost objects, which may include services, customers, projects, or distribution channels. However, to simplify the analysis and ensure alignment with LCA principles, we consider the cost object as the product in this study.

Despite its operational advantages, TD-ABC lacks integration of sustainability indicators, particularly in the social dimension. While extensions like ABC-LCA address environmental impacts, social factors remain underrepresented due to insufficient data on resource provenance and labor conditions, limiting its use for comprehensive social impact assessment.

[7] The consequence of this new calculation approach is that de facto unused time is freed up. In other words, certain resources appear not to be mobilized in the context of the activities actually carried out. The model thus isolates "unused capacity". In management literature, this unused capacity is also called "slack", but companies should try to reduce it. In some cases, unused capacities have also to be related with risk analysis, in order to face extreme and critical events.

This study addresses that gap by proposing the integration of S-LCA into TD-ABC, creating a unified framework—TD-ABC-S-LCA—that can serve both operational accounting and stakeholder-oriented sustainability assessments.

Integrating S-LCA into TD-ABC appears relevant, firstly because social LCA uses time as TD-ABC even if it's used in a different way; secondly, because social LCA is supposed to provide and capture a full range of impacts; and thirdly, because both approaches rely on matrix-based structures, facilitating coherent and operational integration (Sonnemann and Margni, 2015).

While prior studies focus on monetizing social aspects (Abou Taleb and Al Farooque, 2021; Roos Lindgreen and Vermeulen, 2023), or on advocating for better integration of social dimensions within cost accounting methodologies (von Braun and Hendriks, 2023), no existing model has successfully operationalized the integration of S-LCA with cost accounting approaches. To our knowledge, this study is the first to propose an operational integration of S-LCA into TD-ABC, leveraging shared time-based and matrix-based structures to enable managerial relevance, system compatibility, and real-world implementation.

To overcome these challenges, our framework proposes embedding S-LCA indicators into TD-ABC, using time-based and cost data already available within companies' internal systems. This approach significantly reduces the time and effort required for data collection, ensures the use of company-specific information, and allows social impacts to be evaluated in direct connection with managerial accounting processes, bridging the gap between sustainability assessment and operational decision-making. The calculation methodology of TD-ABC is further detailed in Appendix 5-1. Figure 5-3 provides a graphical representation of the TD-ABC structure, adapted from Kaplan & Anderson (2004).

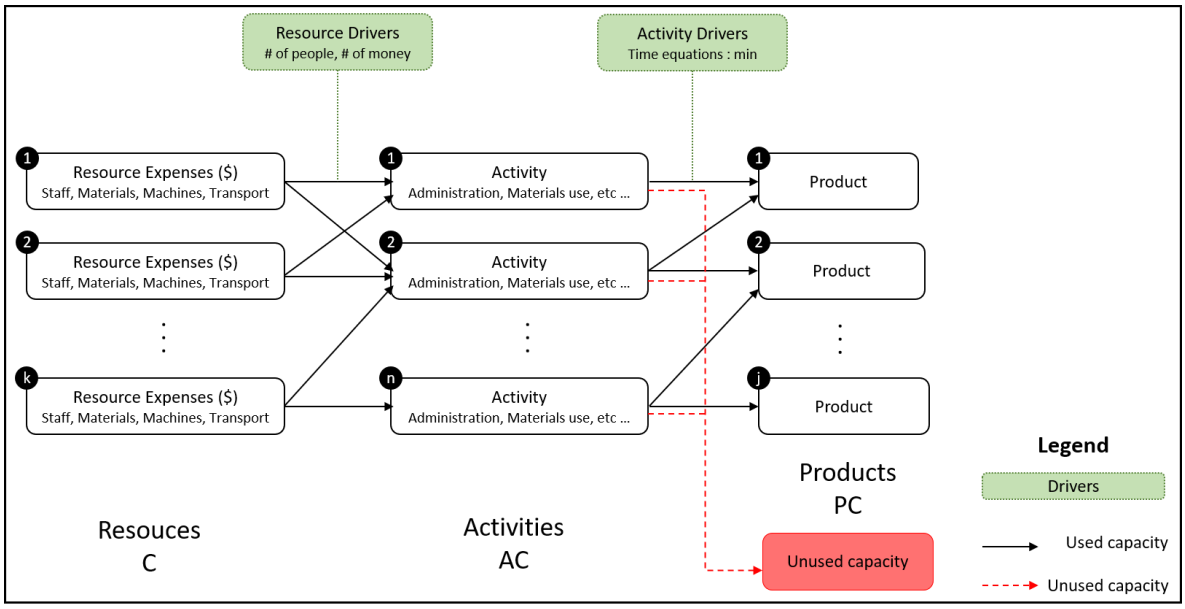


Figure 5-3 Graphic Representation of TD-ABC (adapted from Kaplan and Anderson (2004))

C refers to the cost of a resource k, AC refers to the cost of an activity n and PC refers to the cost of a product j

II. Materials and Methods

II.1 Methodological Contribution

The integration of S-LCA with the TD-ABC model facilitates the incorporation of social impact data while retaining the computational structure of the TD-ABC framework. This integration shifts the focus from high-level accounting and social evaluations at the organizational level to more detailed assessments at the activity and product levels, guided by activity and product drivers from TD-ABC. By analyzing activities and products, this approach also enables a re-examination of the resources mobilized, considering the social conditions under which they are produced or used. This integrated model, referred to as TD-ABC-S-LCA, enables granular, activity-driven insights that support socially responsible decision-making at both the activity and product levels. The methodological framework covers the four phases of S- LCA specified in reference standards ISO 14075 (2024), ensuring robust, multidimensional analysis. A common glossary for an integrated framework combining ABC and LCA was proposed by Jourdaine et al. (2021) and is used in the present paper (Appendix 5-2).

II.1.1 Goal and Scope Definition

This methodology is designed to be applied at the organization scale, with the objective of allocating both direct and indirect upstream social impacts associated with the company to the products it generates. This methodology ensures the alignment of the scope and computational structure of both methodologies, facilitating their integration into a unique management tool that provides economic and social insights. This phase establishes the purpose of the assessment study and defines the scope including the system boundaries, functional unit, the applied assessment approach and key social impact categories and stakeholders to be evaluated. The methodology ensures that resources, activities, and associated impacts are comprehensively aligned between the two systems. In TD-ABC, resources are implicitly accounted for within resource costs. The integration extends this to include social impacts relevant to each resource, ensuring conceptual consistency between two methodologies. In this study, “resource” refers to economic inputs acquired for activities in the TD-ABC framework, such as labor, materials, or services, and should not be confused with 'resource' in LCA, which typically refers to natural resources extracted from the environment.

The methodology aligns social impacts by distinguishing between those direct and indirect to the organization:

- Direct impacts focus on production and operational processes controlled by the company (foreground system) such as manufacturing and assembly as well as supporting processes such as administration and management, often omitted in LCA but essential in TD-ABC.
- Indirect impacts include upstream activities (background system), such as raw material extraction and supply chain processes, are included through detailed social inventory data. Downstream activities (e.g., product use and end-of-life) are excluded to align with the scope of the TD-ABC framework.

The system boundary encompasses a cradle-to-gate perspective, incorporating all stages from raw material acquisition to manufacturing. The integration of S-LCA and TD-ABC aims to provide a unified framework for assessing both direct and indirect social impacts associated with resource use and organizational activities. Furthermore, the approach is designed to be scalable, maintaining the robustness of each methodology while extending their applicability to new organizational contexts and diverse case studies.

II.1.2 Social Life Cycle Inventory (S-LCI)

This phase involves data collection across the product life cycle. The objective of the S-LCI is to gather and evaluate relevant data on social conditions and risks as defined during the scope definition (Jørgensen et al., 2008). It is one of the most resource-intensive and methodologically challenging phase of S-LCA (Bouillass et al., 2021), particularly when attempting to reflect real-world supply chain complexity.

In the TD-ABC-S-LCA framework, S-LCI construction is informed by both cost-accounting and social data structures. Specifically, we use data obtained through the TD-ABC approach—such as resource costs, capacity cost rates, time required to complete activities, and resource and activity drivers—and link them with social risk data provided by an input-output-based Social LCA database. In this study, PSILCA 3.1 – Starter (cut-off 1e-5, worker hours) is used, and calculations are performed based on worker hours as the activity variable.

The activity variable is “worker hours”, representing the labor time (in hours) required to complete specific activities within the production process, enabling the connection between time-based cost accounting and risk-based social metrics. The S-LCI is automatically computed by combining the TD-ABC framework with PSILCA data, enabling a systematic and streamlined evaluation of social impacts. This integration allows for a more detailed and accurate analysis of resource use and its social implications. The aim is to enhance data quality by prioritizing specific, activity data, rather than solely on generic datasets. This allows for improved representation of social impacts and ensures a robust

foundation for subsequent assessment phases, particularly when linking impacts to specific cost drivers and decision-making processes.

While PSILCA was selected for the purposes of this study, the methodology remains compatible with other monetary input-output databases, such as SHDB, provided that social impact indicators are expressed per unit of economic output (e.g., per dollar or euro). SO-LCA, by contrast, is based on physical flow modeling and is not suitable for integration into the TD-ABC approach, although it may be applicable to ABC-LCA model (Jourdaine et al., 2021).

Furthermore, to address limitations associated with generic datasets, we recommend that practitioners complement database results with grounded studies and primary data collection, particularly from suppliers, as well as region-specific or process-specific sources within the supply chain. This hybrid approach enhances data quality by tailoring the social inventory to the company's actual operational conditions, helping ensure that the S-LCI reflects real-world practices and local risks. As a result, the analysis gains in both accuracy and relevance, enabling more targeted and actionable insights for decision-makers.

II.1.3 Social Life Cycle Impact Assessment (S-LCIA)

This phase aims to compute the social impact indicators using the collected data from the S-LCI phase. It consists of computing the medium risk hours by using the "social weighting impact assessment" provided by PSILCA. It converts raw values for each social indicator – by using the total worked hours (considered as the activity variable) and the risk factors (i.e. risk values from very low to very high) in order to assess direct social impacts, and resources costs to the medium risk hours per 1$ output in order to assess direct social impacts, as can be seen on the Figure 5-4. Matrix-based mathematical model was developed to calculate both direct and indirect social impact, explained in the following section.

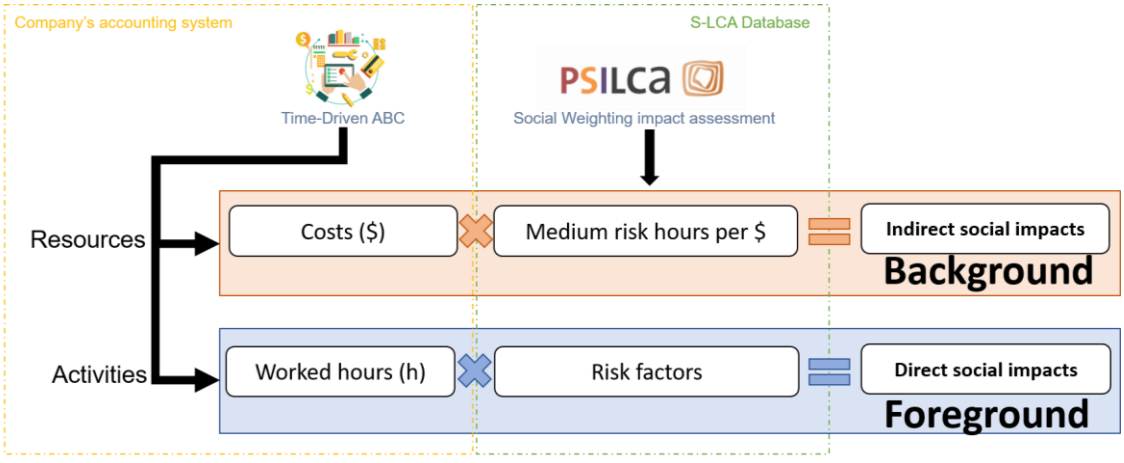


Figure 5-4 Graphical Representation of the S-LCI and S-LCIA Phases (adapted from Lehmann (2023))

II.1.4 Interpretation of the Results

The proposed methodology allows comparing different products based on their social impacts, enabling companies to optimize production strategies to enhance social performance. A contribution tree analysis can visually represent the impacts of various resources and activities, helping to identify critical hotspots and prioritize interventions. Additionally, geographic variability provides insights into how social impacts differ across regions, enabling the development of more context-specific conclusions and actionable recommendations. Finally, unused capacity evaluation can identify inefficiencies in time and resource use to support targeted optimization strategies, ultimately to enhance both operational and social performance.

II.2 Computational Structure of TD-ABC-S-LCA

This section presents the computational structure underlying the integration of S-LCA metrics into TD-ABC methodology. The aim is to provide a systematic approach to allocate economic costs and social impacts across activities and products, enhancing the granularity and accuracy of social impact assessments in decision-making processes.

Figure 5-5 summarizes the four main phases of the TD-ABC-S-LCA methodology detailed in seven steps: (1) Inputs and resource assessment, (2) Activity-level allocation, (3) Product-level calculation, and (4) Handling unused capacity and impact allocation. It illustrates how resource costs and social impacts are progressively traced from inputs to final products, while optionally addressing operational inefficiencies through unused capacity reallocation.

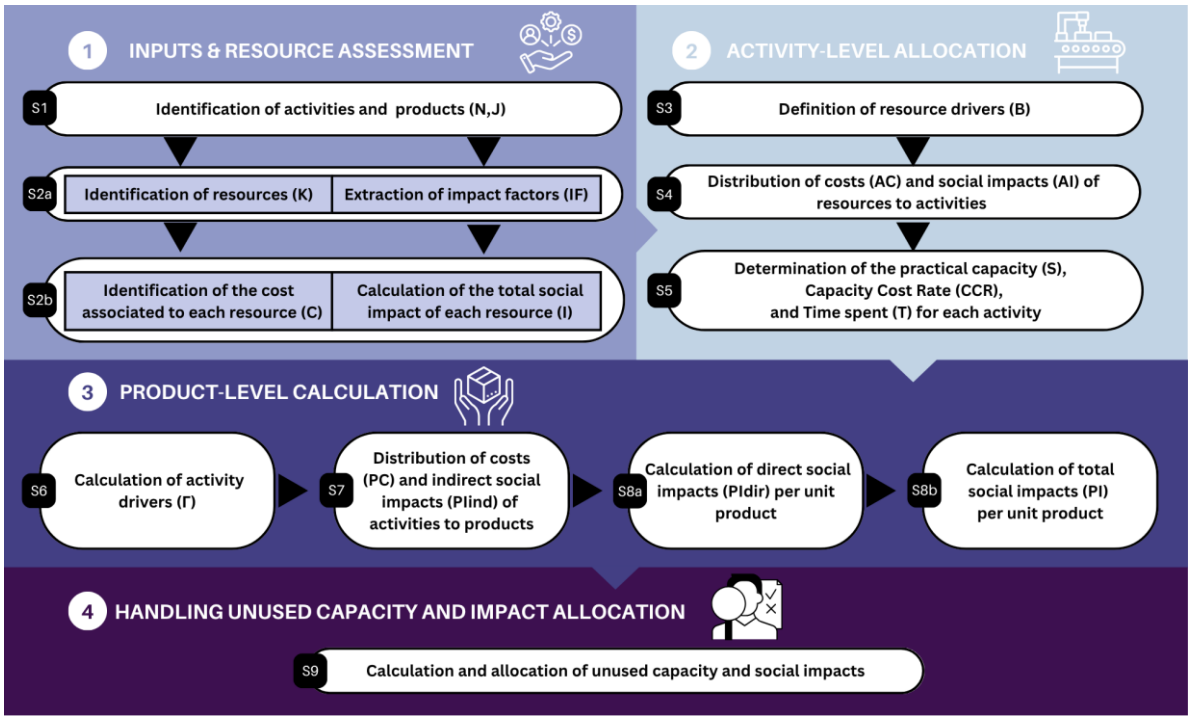


Figure 5-5 Overview of the Proposed TD-ABC-S-LCA Framework

Figure 5-6 illustrates the TD-ABC-S-LCA model, showing the flow from upstream resources (C | CI) through activities (AC | AI) to products (PC | PI). Resource drivers allocate costs and impacts from resources to activities, while activity drivers link activities to products. Unused capacity is highlighted as a key inefficiency. The model focuses on a cradle-to-gate scope, excluding the use phase and end-of-life, with a particular emphasis on integrating social impacts across the value chain.

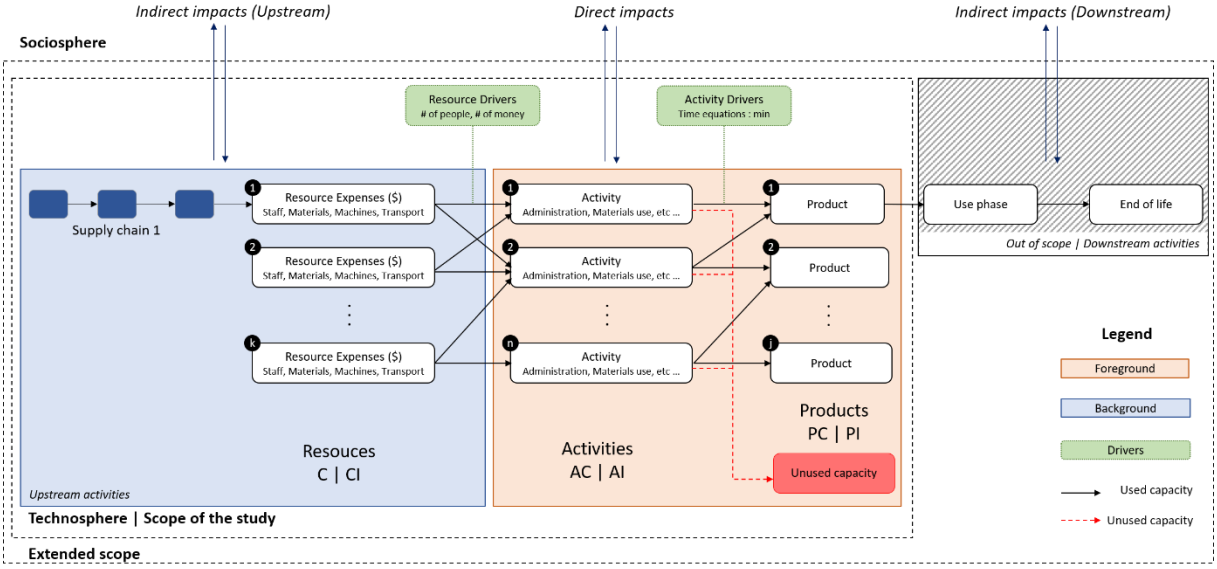


Figure 5-6 Graphical Representation of TD-ABC-S-LCA Model

In this framework, CI represents the impacts of a resource k, AI denotes the impacts of an activity, and PI indicates the impacts of a product j. These impacts can encompass both social and environmental dimensions, with a particular focus on the social dimension in our methodology.

Step 1: Identification of activities and products

This step involves identifying all activities (N), such as production and supporting processes, and products (J) produced by the system and their quantity Q, mapping their relationships to establish a clear framework for analysis. This identification ensures precise allocation of costs and social impacts throughout the production process.

Step 2: Identification of resources and their associated costs, extraction of impact factors, and calculation of social impacts

In this step, the resources used (K) are identified along with their respective geographical locations, as they play a crucial role in determining social impacts. Resources include services, materials, and operational inputs. For each resource, the corresponding social impact factors (IF) are extracted from the PSILCA database, which provides impact metrics per dollar for various categories, enabling a detailed assessment of social implications. Once the resources and their impact factors are identified, the associated costs of each resource are collected and linked to their respective social impacts. This

step ensures that both economic and social dimensions are captured for each resource in the supply chain.

Vector C (k x 1) represents the costs in dollars $ for various resources.

Matrix IF (k x z) contains the social impacts per $1 output for each resource, extracted from the PSILCA 3.1 - Starter database (cut-off 1e-5 | worker hours).

Matrix I (k x z) represents the total social impact of each resource, it's the Hadamard product (Row scaling)[8] of the costs C multiplied by the social impact per 1$ output matrix IF, computed using Equation 5-2.

$$\boldsymbol{C.IF = I}$$

$$\begin{pmatrix} \boldsymbol{c_1} \\ \vdots \\ \boldsymbol{c_k} \end{pmatrix} \times \begin{pmatrix} \boldsymbol{if_{11}} & \cdots & \boldsymbol{if_{1z}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{if_{k1}} & \cdots & \boldsymbol{if_{kz}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{i_{11}} & \cdots & \boldsymbol{i_{1z}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{i_{k1}} & \cdots & \boldsymbol{i_{kz}} \end{pmatrix}$$

Equation 5-2 Resource-Based Social Impact Calculation Using Cost and PSILCA Impact Factors

Step 3: Definition of resource drivers

The resource driver's matrix is a fundamental element of the computational structure, serving to link resources to activities by quantifying the distribution of resource costs and social impacts across operational processes. Derived from the company's accounting system, this matrix provides a detailed breakdown of how each resource contributes to specific activities. Each element represents the proportion or amount of a resource allocated to an activity, ensuring a precise and transparent mapping of resource utilization.

Matrix B (n x k) represents the cost drivers from resources to activities derived from the company's accounting system.

Step 4: Distribution of costs and indirect social impacts of resources to activities

This step involves the distribution of costs (C) and social impacts (I) of resources to activities using the

[8] **Element-wise multiplication – row scaling**, or the Hadamard product row scaling refers to multiplying each row of a matrix A by the corresponding element in a vector v. If A is of size m×n and v is of size m, the resulting matrix maintains the dimensions m×n, but each element in row i of A is scaled by the it^{h} element of v. This technique is useful in data normalization and when applying weights to data rows.

resource driver's matrix (B).

Vector AC (n x 1) represents the costs of activities, it's the Standard matrix multiplication[9] of Matrix B and vector C, computed using Equation 5-3.

$$\boldsymbol{B.C = AC}$$

$$\begin{pmatrix} \boldsymbol{b_{11}} & \cdots & \boldsymbol{b_{1k}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{b_{n1}} & \cdots & \boldsymbol{b_{nk}} \end{pmatrix} \times \begin{pmatrix} \boldsymbol{c_1} \\ \vdots \\ \boldsymbol{c_k} \end{pmatrix} = \begin{pmatrix} \boldsymbol{ac_1} \\ \vdots \\ \boldsymbol{ac_n} \end{pmatrix}$$

Equation 5-3 Allocation of Resource Costs to Activities Using Resource Drivers

Matrix AI (n x z) represents the total indirect social impact of each activity, it's the standard matrix multiplication of matrix B and I, computed using Equation 5-4.

$$\boldsymbol{B.I = AI}$$

$$\begin{pmatrix} \boldsymbol{b_{11}} & \cdots & \boldsymbol{b_{1k}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{b_{n1}} & \cdots & \boldsymbol{b_{nk}} \end{pmatrix} \times \begin{pmatrix} \boldsymbol{i_{11}} & \cdots & \boldsymbol{i_{1z}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{i_{k1}} & \cdots & \boldsymbol{i_{kz}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{ai_{11}} & \cdots & \boldsymbol{ai_{1z}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{ai_{n1}} & \cdots & \boldsymbol{ai_{nz}} \end{pmatrix}$$

Equation 5-4 Allocation of Indirect Social Impacts to Activities

Step 5: Determination of practical capacity, Capacity Cost Rate CCR and time estimation

The determination of practical capacity and time estimation is a fundamental step in the Time-Driven Activity-Based Costing (TD-ABC) methodology, as it lays the groundwork for accurate cost and impact allocation. Practical capacity (S) refers to the realistic amount of working time available for resources, accounting for everyday constraints such as vacations. This ensures the capacity used in the analysis is not just theoretical but reflects actual operational conditions. In parallel, time estimation (T) focuses on determining how long each activity takes based on its unique characteristics and operational requirements. Central to this process is the Capacity Cost Rate (CCR) a key metric calculated by dividing the total cost of a resource group by its practical capacity, providing the cost per unit of available

[9] **Standard matrix multiplication** involves taking the dot product of rows and columns. For matrices A (of size m×n) and B (of size n×p), the resulting matrix C (of size m×p) is computed by multiplying each element of the rows of A with the corresponding elements of the columns of B and summing these products. This operation is crucial for many applications in mathematics and computer science, including solving linear equations and transforming geometric data.

operational time. The CCR ensures precise cost allocation, reflects realistic resource utilization.

We define the following:

Matrix T (j x n) derived from Time-Driven Activity-Based Costing (TD-ABC) table, this matrix represents the time spent on each activity n to produce product j.

Row vector S (1 x n) represents the annual practical capacity of each activity in terms of time.

Vector CCR (n x 1) calculated by dividing the total cost of the activity (vector AC) by the practical capacity (S) of the activity.

Step 6: Calculation of activity drivers

This step focuses on the computation of the activity drivers matrix Γ, which represents the drivers linking activities to products. It quantifies the proportion of each activity's time allocated to the production of specific products, enabling precise distribution of costs and social impacts.

Matrix Γ (j x n) represents the cost drivers from activities to products, computed using Equation 5-5, calculated by dividing the time spent on each activity (T) by the practical capacity of that activity (S).

$$\boldsymbol{\Gamma} = \frac{\mathbf{T}}{\mathbf{S}}$$

$$\begin{pmatrix} \boldsymbol{t_{11}} & \cdots & \boldsymbol{t_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{t_{j1}} & \cdots & \boldsymbol{t_{jn}} \end{pmatrix} : \begin{pmatrix} \boldsymbol{s_1} & \dots & \boldsymbol{s_n} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\gamma_{11}} & \cdots & \boldsymbol{\gamma_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\gamma_{j1}} & \cdots & \boldsymbol{\gamma_{jn}} \end{pmatrix}$$

Equation 5-5 Computation of Activity Drivers Linking Activities to Products

Step 7: Distribution of costs and indirect social impacts of activities to products

This step involves the distribution of costs (AC) and social impacts (AI) of activities to products using the activity drivers matrix (Γ).

Matrix PI_{ind} (j x z) represents the indirect social impacts of each unit product, it's the Standard matrix multiplication of Matrix Γ and AI, computed using Equation 5-6.

$$\boldsymbol{\Gamma} \,.\, \boldsymbol{AI} = \boldsymbol{PI_{ind}}$$

$$\begin{pmatrix} \boldsymbol{\gamma_{11}} & \cdots & \boldsymbol{\gamma_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\gamma_{j1}} & \cdots & \boldsymbol{\gamma_{jn}} \end{pmatrix} \times \begin{pmatrix} \boldsymbol{ai_{11}} & \cdots & \boldsymbol{ai_{1z}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{ai_{n1}} & \cdots & \boldsymbol{ai_{nz}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{pi_{ind_{11}}} & \cdots & \boldsymbol{pi_{ind_{1z}}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{pi_{ind_{j1}}} & \cdots & \boldsymbol{pi_{ind_{jz}}} \end{pmatrix}$$

Equation 5-6 Allocation of Activity-Level Social Impacts to Products

Matrix PC (j x n) represents the cost of each activity per product in dollars $. It could be calculated using two formulas:

- The first formula was previously established by Jourdaine et al. (2021) from an ABC perspective to calculate total costs of each product category (PC), computed using Equation 5-7.

$$\boldsymbol{\Gamma} \,.\, \boldsymbol{AC} \;=\; \boldsymbol{PC}$$

$$\begin{pmatrix} \boldsymbol{\gamma_{11}} & \cdots & \boldsymbol{\gamma_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\gamma_{j1}} & \cdots & \boldsymbol{\gamma_{jn}} \end{pmatrix} \times \begin{pmatrix} \boldsymbol{ac_1} \\ \vdots \\ \boldsymbol{ac_n} \end{pmatrix} = \begin{pmatrix} \boldsymbol{pc_{11}} & \cdots & \boldsymbol{pc_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{pc_{j1}} & \cdots & \boldsymbol{pc_{jn}} \end{pmatrix}$$

Equation 5-7 Activity-Based Cost Allocation to Products (ABC-LCA Method)

- The second formula can be derived using the TD-ABC approach using the Capacity Cost Rate CCR. And the cost of each activity per product in $ could be calculated using Equation 5-8.

$$\boldsymbol{T} \,.\, \boldsymbol{CCR} \;=\; \boldsymbol{PC}$$

$$\begin{pmatrix} \boldsymbol{t_{11}} & \cdots & \boldsymbol{t_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{t_{j1}} & \cdots & \boldsymbol{t_{jn}} \end{pmatrix} \times \begin{pmatrix} \boldsymbol{ccr_1} \\ \vdots \\ \boldsymbol{ccr_n} \end{pmatrix} = \begin{pmatrix} \boldsymbol{pc_{11}} & \cdots & \boldsymbol{pc_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{pc_{j1}} & \cdots & \boldsymbol{pc_{jn}} \end{pmatrix}$$

Equation 5-8 TD-ABC Cost Allocation to Products Using Capacity Cost Rates

Step 8: Calculation of total social impacts per unit product

The previously calculated and distributed social impacts, flowing from resources to activities and subsequently to products, represent the indirect upstream impacts associated with the background system. In contrast, the direct social impacts, linked to the foreground system and specific operational activities, are calculated in this step to provide a comprehensive assessment.

First, the company conducts a study to determine the risk level for each impact category. Then, using PSILCA, each risk level is assigned a corresponding factor RF[10] (e.g., very low risk = 0.01, low risk = 0.1, etc.). To calculate the direct social impact for each product unit, the total time spent producing each product j ($\sum_{x=1}^{n} t_{jx}$), which is extracted from the TD-ABC table, is multiplied by the factor associated with the corresponding risk level. It is important to convert the time from minutes to hours, as the final result will be expressed in medium risk hours. PI_{dir} represents the direct social impacts of each unit product, calculated using Equation 5-9.

[10] Risk Factor (RF) extracted from PSILCA: Very low risk (0.01), Low risk (0.1), Medium risk (1), High risk (10), Very high risk (100), No risk/opportunity (0), Low opportunity (0.1), Medium opportunity (1), High opportunity (10), No data (0.1)

$$\begin{pmatrix} \sum_{x=1}^{n} t_{1x} \\ \vdots \\ \sum_{x=1}^{n} t_{jx} \end{pmatrix} \times \boldsymbol{RF} = \boldsymbol{PI_{dir}}$$

Equation 5-9 Calculation of Direct Social Impacts Using Time-Driven Risk Weighting

Matrix PI (j x z) represents the total social impacts per product, calculated as the sum of the matrix of indirect impacts PI_{ind} with of the matrix of direct impacts PI_{dir}, computed using Equation 5-10. This comprehensive measure ensures a complete evaluation of social impacts across the product's life cycle.

$$\boldsymbol{PI_{ind} + PI_{dir} = PI}$$

$$\begin{pmatrix} pi_{ind_{11}} & \cdots & pi_{ind_{1z}} \\ \vdots & \ddots & \vdots \\ pi_{ind_{j1}} & \cdots & pi_{ind_{jz}} \end{pmatrix} + \begin{pmatrix} pi_{d_{11}} & \cdots & pi_{d_{1z}} \\ \vdots & \ddots & \vdots \\ pi_{d_{j1}} & \cdots & pi_{d_{jz}} \end{pmatrix} = \begin{pmatrix} pi_{11} & \cdots & pi_{1z} \\ \vdots & \ddots & \vdots \\ pi_{j1} & \cdots & pi_{jz} \end{pmatrix}$$

Equation 5-10 Aggregation of Direct and Indirect Social Impacts per Product

Step 9: Calculation and allocation of unused capacity and social impacts

Unused capacity represents the difference between the available practical capacity of an activity and the actual capacity used during production process. Equation 5-11 quantifies this gap by calculating the proportion of unused capacity for a given activity as follows:

$$unused\ capacity\ of\ an\ activity\ y = 1 - \frac{\sum_{x=1}^{j} T_{x,y} \times Q_x}{S_y}$$

Equation 5-11 Quantification of Unused Activity Capacity

where $T_{x,y}$ is the time required for activity y for product x , Q_x (j x 1) is the annual quantity of product x , and S_y is the annual practical capacity of activity y. Integrating this calculation into this research provides critical insights into resource optimization, helping organizations identify underutilized resources and reallocate them effectively to enhance operational efficiency and reduce costs.

While this calculation serves to diagnose inefficiencies, the TD-ABC-S-LCA model optionally extends its scope by reallocating the social and economic impacts associated with unused capacity across products. This redistribution can be performed on a pro-rata basis, either:

- Based on the number of units produced per product category, or
- According to the share of impact (or cost) initially allocated to each product.

This optional step enhances accountability by ensuring that inefficiencies in planning or operations are transparently reflected in product-level assessments. It also supports recommendations in sustainability accounting to internalize indirect impacts. Details and illustrative formulas for this reallocation mechanism are provided in SI.

II.3 Implementation of the TD-ABC-S-LCA Model

The implementation of the TD-ABC-S-LCA framework requires access to structured operational data typically available in organizations with enterprise resource planning (ERP) systems or internal cost-tracking systems. While companies are not required to already use an Activity-Based Costing (ABC) system, having some form of cost accounting structure that tracks time, resource consumption, and activity costs significantly facilitates the implementation. One of the advantages of TD-ABC over traditional ABC is its adaptability to organizations that do not have fully developed ABC models, as it relies on time estimates and capacity cost rates that can be computed from available operational data. Therefore, the model is suitable for organizations with varying levels of cost accounting maturity and can be progressively deployed starting from basic time and cost data.

Table 5-4 summarizes the procedure for implementing the TD-ABC-S-LCA model.

Table 5-4 Stage of TD-ABC-S-LCA Model

Steps	Economic cost (and resulting items / vector / matrix)		Social Impact (and resulting items / vector / matrix)	
1	Identification of activities and products	N, J		
2a	Identification of resources	K	Extraction of impact factors from PSILCA	IF
2b	Identification of the cost associated to each resource	C	Calculation of the total social impact of each resource	I
3	Definition of resource drivers	B		
4	Distribution of costs of resources to activities	AC	Distribution of social impacts of resources to activities	AI
5a	Determination of the practical capacity	S		
5b	Calculation of the Capacity Cost Rate CCR	CCR		
5c	Time Estimation for each activity	T		
6	Calculation of activity drivers	Γ		
7	Distribution of costs of activities to products	PC	Distribution of social impacts of activities to products	PI_{ind}
8a			Calculation of direct social impacts per unit product	PI_{dir}
8b			Calculation of total social impacts per unit product	PI
9	Calculation and allocation of unused capacity and social impacts			

II.4 Application: Case Study

To validate the applicability of the model developed, an illustrative case study was developed, inspired by existing academic applications and refined through expert consultations in the field of sustainability and cost accounting. The scenario reflects a hypothetical but realistic multinational packaging

company, designed to simulate the diverse geographical and operational dimensions typically encountered in the sector. The parameters used are derived from expert-informed assumptions and estimated using time equations in line with TD-ABC principles. These assumptions are explicitly detailed in Appendix 5-3, ensuring transparency and reproducibility of the computational framework. While the data is not drawn from a specific company, the scenario is intended to realistically demonstrate the model's capacity for impact calculation and managerial decision support.

The administrative hub overseeing operations resides in New Zealand (NZ), collaborating closely with external engineers and researchers for product design (Singapore SG) and R&D (Argentina AR). The materials and machinery are purchased from the UK and the US. The manufacturing and technical core are based in the UK, housing two production activities: the production of paper Packaging and of plastic packaging. The final product line-up comprises: α a recycled paper-based packaging, β a non-recycled paper-based packaging and γ a plastic-based packaging. The resolution of the case study follows the approach outlined in the steps below:

II.4.1 Goal and Scope Definition

The main goal of the S-LCA in this study is to support this company in reducing the social impacts of its value chain and products. This is achieved by conducting a comparative analysis of three packaging products, identifying the most impactful activities and resources, and mapping their associated geographical locations through a variability analysis. The functional unit could be defined as "the production of one unit of each packaging product type (α, β, γ)" from cradle-to-gate process, encompassing raw material acquisition, transport, and manufacturing (from a supply chain perspective). This functional unit allows for a comparative analysis of the social impacts associated with each packaging type across the value chain. Figure 5-7 simplifies the perimeter of the study.

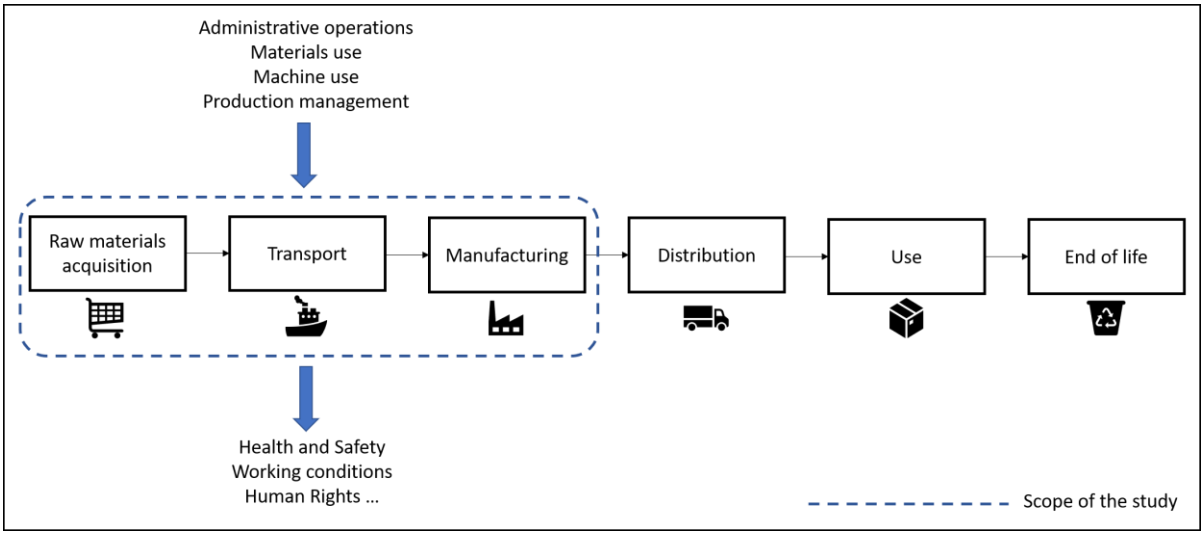


Figure 5-7 Perimeter of the Study

To determine the impact categories, all PSILCA indicators were initially considered; based on a comprehensive literature review of S-LCA in the packaging sector and insights from expert consultancy, 25 indicators were selected for further analysis. Among these, the 10 most significant impact categories were evaluated to ensure a focused and relevant assessment. These key impact categories, including fair salary, public sector corruption and others, are presented in Table 5-5.

Table 5-5 Impact Category Selected for The Study

Impact categories	**Abbreviation**	**Unit**
Certified environmental management system	CMS	CMS med risk hours
Fair Salary	FS	FS med risk hours
Gender wage gap	GW	GW med risk hours
Indigenous rights	IR	IR med risk hours
Industrial water depletion	WU	WU med risk hours
Promoting social responsibility	PSR	PSR med risk hours
Public sector corruption	C	C med risk hours
Trade unionism	TU	TU med risk hours
Value added (total)	VAT	VAT med risk hours
Violations of employment laws and regulations	VL	VL med risk hours

The innovation of this method is in the second and third phases: The Social Life Cycle Inventory (S-LCI) and the Social Life Cycle Assessment (S-LCA). The data for the case study is presented in SI.

To meet the goal of the present case study, the interpretation of results is performed following various steps. First a comparison of social performance of the three products is illustrated and discussed. Furthermore, a contribution analysis allows for identifying the most contributing activities and resources for the highest social risks. Based on the identified processes, a variability analysis is performed by considering different geographical locations for the most contributing processes. This enables for identifying future improvements for the overall social performance. Finally, from a management perspective, the unused capacity is assessed to highlights inefficiencies in resource utilization. This step provides valuable insights for reallocating underutilized resources, thereby improving operational efficiency and reducing associated social and economic impacts.

II.4.2 S-LCI and S-LCIA

The application of the methodologies described in Section II.2 to the case study follows a detailed stepwise approach covering 8 steps. Given the procedural complexity and the inclusion of numerous tables and calculations, the full implementation is provided in Appendix 5-3 which enhances clarity and ensures reproducibility and transparency.

Step 1: Identification of activities and products

In this case study, the key activities involved are as follows: a1. Administration, a2. Materials use for α, a3. Materials use for β, a4. Materials use for γ, a5. Machine use for paper packaging, a6. Machine use for plastic packaging, a7. Production management.

The company's product line includes three packaging types: α a recycled paper-based packaging, β a non-recycled paper-based packaging and γ a plastic-based packaging.

Step 2: Identification and valuation of resources and their social impacts

The resources used in this case study, along with their geographical location, are as follows: Cleaning service (UK), Communication (NZ), Electricity (NZ), Electricity (UK), Industrial equipments (USA), IT service (NZ), labour costs : salary & benefits, Legal service (NZ), Marketing (NZ), Paper mills (USA), Paperboard mills (USA), Plastics packaging materials (USA), Product design service (SG), R&D (AR), Recycled paper and cardboard (UK), Road freight (UK), Sea freight (USA), Softwares & systems (JP).

The supply chain mapping for α, β, and γ production is illustrated in Figure 5-8. The extraction of a PSILCA-based social impact profile and costs for each resource is detailed in Appendix 5-3.

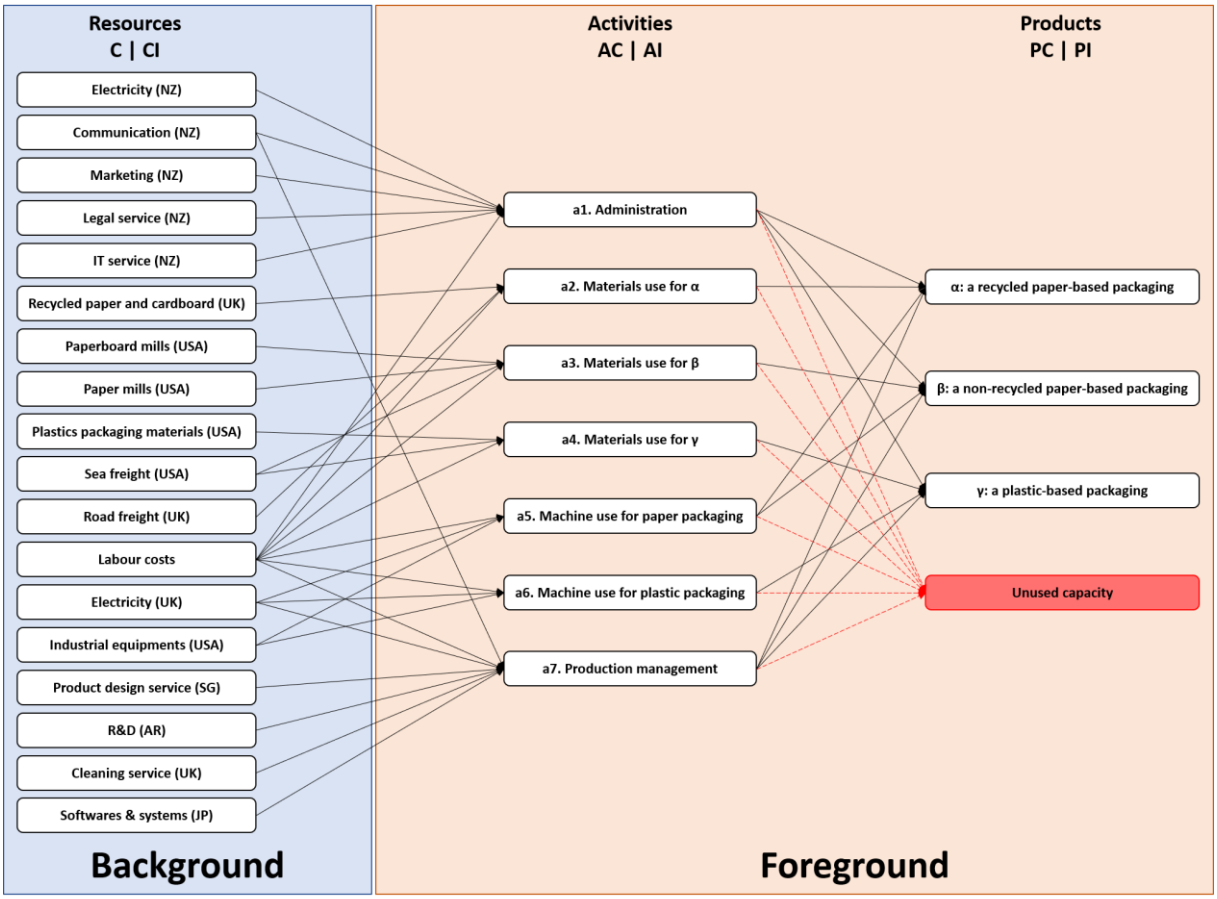


Figure 5-8 Supply Chain Mapping for α, β, and γ Production

Step 3–4 map these resources to activities using cost drivers, then to products using time-based drivers derived from time equations provided by experts.

Step 5–6 calculate practical capacity and capacity cost rates (CCR) per activity, and assign activity durations using TD-ABC time equations (e.g., a1. Administration = 1 + 0.3 {if non-recycled paper} + 0.7 {if recycled paper}) .

Step 7–8 compute indirect and direct social impacts per unit product. Indirect impacts result from upstream resource flows, while direct impacts are calculated using risk factors associated with sectoral practices.

The model provides product-specific cost breakdowns and social impact values across ten impact categories (e.g., Fair Salary, Public Sector Corruption, Trade Unionism) (Table 5-6). These impacts are disaggregated into contributions from each activity and resource, enabling contribution analysis and identification of social hotspots. Finally, the study includes an unused capacity calculation (Step 9) for each activity and proposes an optional reallocation of its associated impacts across products (see Section III.5 and SI. This detailed case study demonstrates the feasibility of implementing the TD-ABC-S-LCA model in an operational context, using expert-informed assumptions and structured data to provide actionable insights.

Table 5-6 Total Social Impacts (PI) of Each Product

Total social impacts (PI)	**Unit**	**α**	**β**	**γ**
Certified environmental management system	CMS mrh†	3.65	7.99	5.01
Fair Salary	FS mrh	9.69	19.10	15.75
Gender wage gap	GW mrh	5.18	3.94	3.25
Indigenous rights	IR mrh	3.90	3.55	2.79
Industrial water depletion	WU mrh	2.26	7.87	6.52
Promoting social responsibility	PSR mrh	3.20	5.13	2.53
Public sector corruption	C mrh	19.69	21.03	18.58
Trade unionism	TU mrh	7.68	11.85	9.80
Value added (total)	VAT mrh	5.72	6.23	5.13
Violations of employment laws and regulations	VL mrh	2.77	7.94	6.62

III. Results

This section highlights the types of results achievable through this methodology. It begins with a comparative analysis of products, evaluating their cost and time efficiency, and associated social impacts.

Next, a contribution analysis of activities and resources can identify the processes that contribute most significantly to these impacts. Finally, the influence of geographic variability on social outcomes can be examined.

III.1 Cost and Time Efficiency Analysis

Figure 5-9 compares the cost and time efficiency of three packaging types. Non-recycled paper is the most time-consuming and costly, making it the least efficient. Recycled paper is slightly more time-efficient but marginally more expensive than non-recycled. Plastic packaging offers the lowest cost while matching recycled paper in production time.

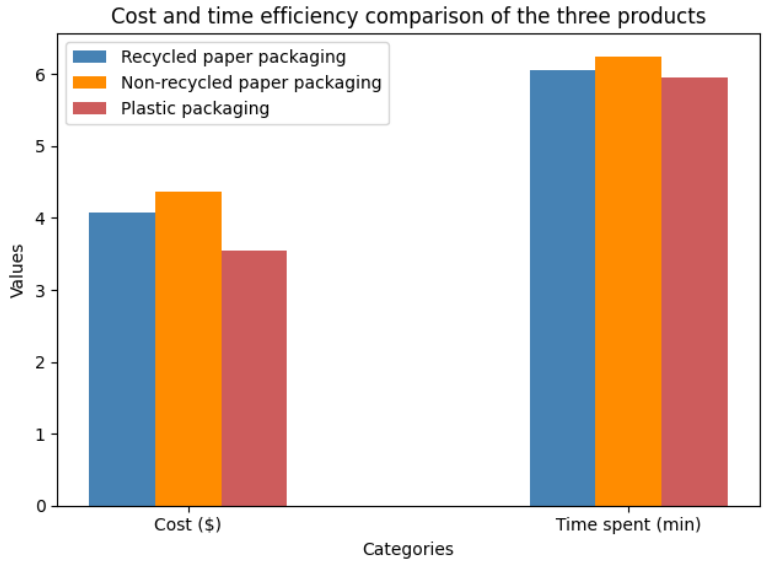


Figure 5-9 Comparison of Three Packaging Types Based on Cost and Time Efficiency

The optimal choice among the three packaging types depends on the company's priorities, whether to minimize costs, optimize time, enhance social sustainability or balance among these factors. Given that cost and time factors are closely matched, the company decided to base their choice on social performance. In the next part, the three packaging types will be compared based on their social impacts.

III.2 Social Impact Assessment: Comparative Analysis

Figure 5-10 illustrates a comparison of the three packaging types across different social impacts. It reveals that "Fair salary" and "Public sector corruption" are most critical social indicators with both showing high medium risk hours across all packaging types. These issues represent key areas where the company faces significant social sustainability challenges.

Recycled paper packaging is the most socially preferable option, with the lowest risks across key indicators. Plastic packaging ranks between recycled and non-recycled paper, presenting moderate

risks in areas like “Fair salary” and “Trade unionism”. Non-recycled paper consistently shows the highest risk levels, making it the least desirable choice.

Additionally, in the “Industrial water depletion”, “Violations of labor laws and regulations”, and “Fair salary” categories, the risks are quite high for both non-recycled paper packaging and plastic. These elevated risks are notably related to the raw materials acquired from the USA. The contribution is immense to these social areas of impact.

In the next section, a contribution analysis is conducted to further examine the distribution of social impacts across the different packaging types. Key processes contributing most significantly to the overall social risks associated with non-recycled paper packaging, which has been identified as higher-risk option compared to recycled paper and plastic packaging, will be identified.

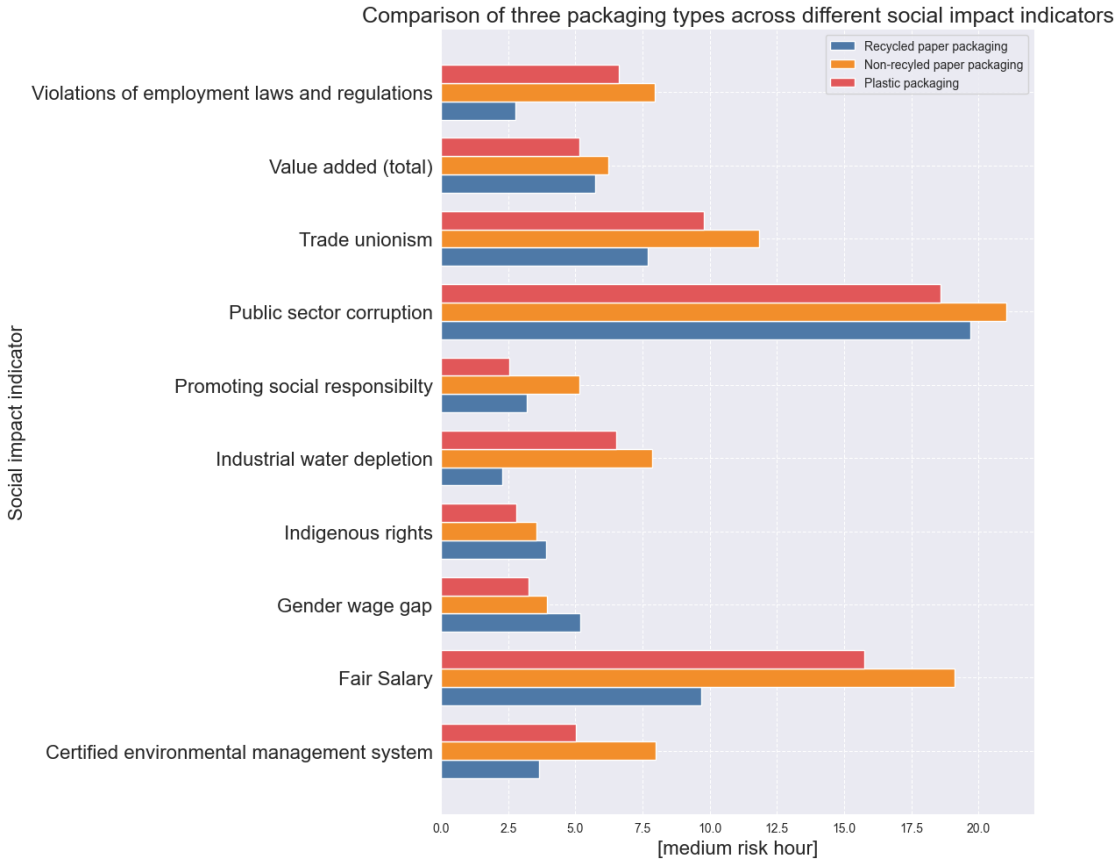


Figure 5-10 Comparison of Three Packaging Types Across Different Social Impact Indicators

III.3 Contribution Analysis

After identifying the distribution factors or drivers from resources to activities (activity drivers) and from activities to products (product drivers), it becomes possible to determine inverse factors, known as the contribution factor. This approach assesses the contribution of activities to the social impacts of products and evaluates how resources influence these impacts.

III.3.1 Activities Contribution

CA_j (n x z) represents the contribution matrix used to assess the social impact of activities on the social impact of product j, as calculated using Equation 5-12.

$$\frac{\boldsymbol{AI}}{\boldsymbol{AC}} \times \mathbf{PC_j} = \boldsymbol{CA_j}$$

Equation 5-12 Activity Contribution to Product-Level Social Impact

Figure 5-11 provides a contribution tree of non-recycled paper packaging production at the activity level. It shows that materials used for non-recycled paper packaging (a3) is the largest contributor to most social impact indicators, including "Certified environmental management system," "Fair salary," and "Industrial water depletion." Administration (a1) also plays a notable role, particularly in "Value added" and "Fair salary". Smaller contributions are observed for machine use (a5) and production management (a7). Reducing the impacts of materials use (a3) should be prioritized to address the key social risks.

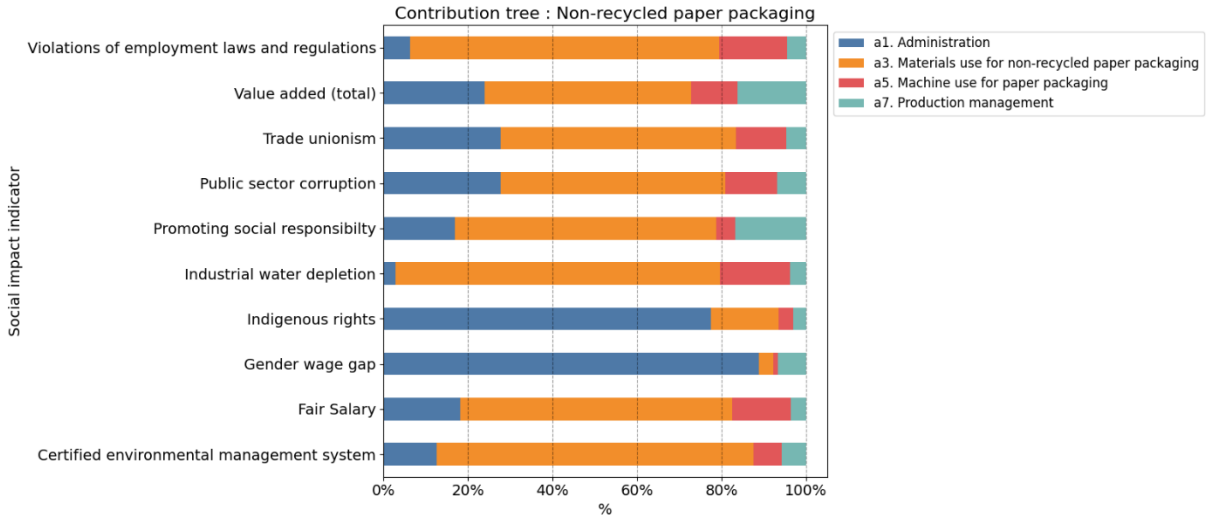


Figure 5-11 Contribution Analysis for Non-Recycled Paper Packaging Production- Activity Level

III.3.2 Resources Contribution

B' (k x n) represents the transposed matrix of B prior to normalization, indicating the contribution of activities to resource impacts.

CR_j (k x z) represents the contribution matrix used to assess the social impact of resources on the social impact of product j, as calculated using Equation 5-13.

$$[\boldsymbol{B'} \times \mathbf{PC_j}] \times \mathbf{IF} = \boldsymbol{CR_j}$$

Equation 5-13 Resource Contribution to Product-Level Social Impact

Figure 5-12 illustrates the contribution of various resources to the production of non-recycled paper packaging. It highlights how different resources influence the overall social and environmental impacts at the resource level.

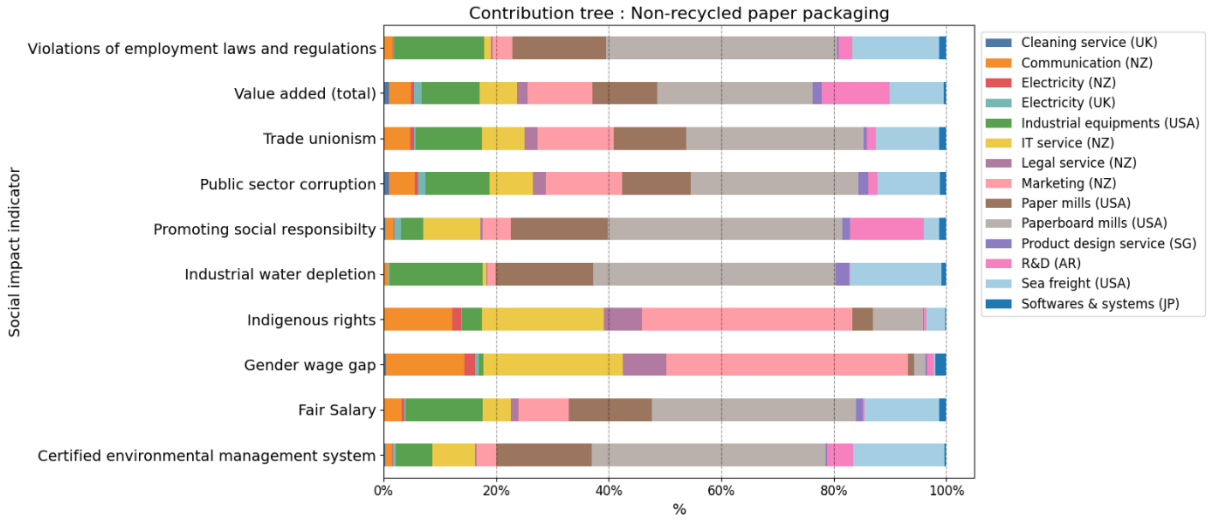


Figure 5-12 Contribution Analysis for Non-Recycled Paper Packaging Production – Resource Level

For non-recycled paper packaging, the production processes of “Paper Mills” and “Paperboard Mills” in the United States (US) are significant drivers of social risks across multiple categories. This process (Paper Mills / Paperboard Mills – US) contributes substantially to risks associated with “Violations of employment laws and regulations”, “Promoting social responsibility”, “Industrial water depletion”, “Fair salary”, and “Public sector corruption”.

The second most identified contributor is “Marketing – NZ” in particular with the categories “Indigenous rights” and “Gender wage gap” which highlights potential governance and equity challenges within this process in NZ.

This contribution tree suggests that the most critical of the social impacts could be significantly mitigated by making targeted improvements in the key processes related to sourcing of raw material. Geographically specific risks, therefore, need to be looked into so as to enhance the overall social sustainability of both non-recycled paper packaging and plastic packaging.

Next, a detailed geographic variability analysis is presented, focusing on the key processes identified as the most significant contributors. The analysis examines how social impacts differ across regions where production activities take place.

III.4 Geographic Variability

Using the PSILCA database, the social risks associated with paper and paperboard production were analyzed across Japan (JP), Great Britain (GB), New Zealand (NZ), and the United States (US).

Figure 5-13 illustrates the heatmaps of the significant social impacts for the selected countries for paper and paperboard production.

The US was found to have consistently high social risks, particularly in “fair salary,” “industrial water depletion,” and “trade unionism”. In contrast, GB demonstrated a more balanced risk profile, with lower risks across most indicators, except for “public sector corruption”. Elevated risks were observed in New Zealand for “public sector corruption”, “fair salary”, and “gender wage gap”, while Japan exhibited moderate risks.

Based on these findings, localizing the sourcing of paper and paperboard to Great Britain is recommended to reduce social risks and transportation impacts by shifting from sea freight to road transport, supporting a more sustainable supply chain. However, using recycled paper remains the better option overall, as it significantly reduces social impacts compared to non-recycled alternatives. Additionally, adopting localized activities in GB can further reduce the social impacts of production while strengthening supplier relationships may lead to better quality, reduced costs, and enhanced Corporate Social Responsibility (CSR).



Figure 5-13 Social Impacts by Country for Paper and Paperboard Production

III.5 Unused Capacity

The analysis of unused capacity across various activities, highlights inefficiencies in resource utilization. The highest unused capacity is observed in administration (15.36%), followed by machine use for paper packaging (13.40%) and materials use for non-recycled paper packaging (12.17%). These percentages indicate that significant portions of practical capacity are underutilized, resulting in operational inefficiencies and potential cost overruns.

Unused capacity in activities such as administration and production management often stems from over-allocation of resources, poor scheduling, or inefficiencies in workflow design. For material usage activities, underutilization may be attributed to fluctuating production demands, supply chain disruptions, or excessive procurement or overstocking of raw materials. These issues highlight the need for better planning and realignment of resource utilization with actual operational requirements. In machine-related activities, common causes include unplanned downtime, extended setup times, or misalignment between production cycles and machine availability.

Additionally, overestimation of practical capacity during the planning phase can exacerbate unused capacity. Kaplan and Anderson (2007) emphasize the importance of aligning practical capacity assumptions with real-world constraints, such as routine maintenance schedules, cleaning requirements, and predictable downtime. Failing to account for these factors often results in overestimated availability and subsequent inefficiencies.

IV. Discussion

This section relies on the results of both the proposed methodology and the case study to discuss the main outcomes of the present paper and assess their potential for generalization to other contexts, as well as how they can inform future research.

IV.1 Methodological Research outcomes

This methodology enables companies to quantitatively assess and compare the social impacts of their products throughout the entire value chain, alongside economic costs and time efficiency. It provides a structured approach to identifying social hotspots across activities and resources. By translating qualitative concerns (e.g., labor rights, fair salary) into quantitative metrics, it helps objectify social impacts and potentially respond more transparently to stakeholder expectations. Additionally, it facilitates the analysis of geographical variability by mapping social impacts across different regions, helping organizations identify risks and opportunities within their supply chains. It also allows for testing various use cases and organizational scenarios, enabling the evaluation of variations in social impacts across contexts or operational changes.

To effectively implement this methodology, companies need access to cost and operational data (i.e., resources used by each activity, time spent, and associated costs) as well as basic knowledge of TD-ABC and S-LCA principles. Despite the existence of TD-ABC models in academic literature, their actual use in industry remains limited, which made it difficult to identify a real-world case for testing the proposed methodology.

The model structure has been designed to be easily transferable into ERP systems or dedicated software, ensuring compatibility with existing internal management tools. An Excel-based tool has

been developed to facilitate its application and can be tailored to the company's needs, allowing users to input cost and time data and compute social impact metrics.

The results generated by this methodology can be leveraged in various ways. Companies can use the insights to optimize supply chain decisions, strengthen supplier relationships, and improve workforce management by addressing key social risks such as fair wages and labor rights violations. The methodology also enables direct and indirect social impact differentiation, which is particularly useful for organizations seeking to improve their Scope 1, 2, and 3 social impact assessment. Furthermore, the information obtained can further be integrated within other frameworks, such as the Digital Passport Product, to enhance the transparency of products in terms of social sustainability. Certain activities could also be steered toward circular economy practices, supporting the redesign of supply chains and business models aligned with social and environmental value creation.

The proposed methodology was successfully implemented in the present study, which allowed for several improvements for both the S-LCA method and TD-ABC as an accounting approach. TD-ABC helps to improve quality of foreground data by introducing specific data from the company. This can lead to more accurate social impact assessment and thus helps enhance the S-LCI phase by addressing gaps related to data procurement.

The integration of S-LCA metrics into TD-ABC is compatible with monetary input-output databases such as PSILCA and SHDB, as long as social impact indicators are expressed per unit of economic output (e.g., per dollar or euro). This flexibility ensures that the model is not dependent on a single data source and can be adapted to different datasets depending on user needs.

However, we acknowledge that relying on generic databases like PSILCA introduces certain limitations, particularly regarding geographic specificity, sectoral granularity, and supplier-level accuracy. To address these limitations, we recommend using PSILCA primarily as a screening tool during initial assessments. Where feasible, companies are encouraged to complement generic results with grounded data—such as region-specific, process-specific, or supplier-specific information—to improve precision and decision-making relevance.

Databases like SO-LCA, which are based on physical flows, are not compatible with the TD-ABC framework. Instead, they may be more suitable for integration with frameworks like ABC-LCA (Jourdaine et al., 2021), which can accommodate physical input structures, to combine environmental and social dimensions. Therefore, the selection of the database must align with the nature of the accounting framework used.

Additionally, the proposed framework can be easily extended to environmental LCA through any environmentally extended input-output (EEIO) database, such as Exiobase. Exiobase provides environmental impact data per monetary unit (€) for various activities across countries, reducing the reliance on time-consuming physical data collection for assessing resource-related environmental impacts (Jourdaine et al., 2021). This aligns with recent developments in accounting for climate-related performance, as advocated by Kaplan and Ramanna (2021), emphasizing the importance of embedding environmental and social considerations into managerial control systems.

Finally, the integration of the unused capacity calculation into the methodology enhances resource assessment by identifying unused capacities across activities, accounting for real-world constraints like downtime for maintenance, cleaning cycles, and production setup times. This aligns with TD-ABC principles, providing precise insights into operations. To prevent companies from avoiding accountability for these impacts and to discourage opportunistic behavior, an effective measure could be to reallocate the environmental and social impacts of unused capacities to the products. Companies could achieve this through a pro-rata approach based on either production quantities or the associated impacts (as mentioned in SI). This strategy would incentivize companies to actively minimize such inefficiencies, particularly if customers are informed and responsive to these considerations. Ultimately, this fosters optimized resource use, greater accountability, and the advancement of sustainable business practices.

Moreover, it is important to reiterate that the present framework operates within a cradle-to-gate system boundary, in alignment with the core structure of TD-ABC models. By design, ABC-based cost accounting systems do not extend to the use phase or end-of-life stages, which are typically external to the operational and financial control of the organization. Although this may limit the comprehensiveness of social impact coverage, especially for products like packaging, the scope is consistent with the model's internal decision-support function. Future studies may consider complementing this approach with downstream-focused tools to assess impacts related to consumption and disposal stages.

While the proposed method contributes to better integration of social impacts within cost accounting approaches, some limitations can be highlighted. A generic database for S-LCA is here used to facilitate the implementation of the method, which can be limited to ensure accurate decisions for a company as social indicators can vary significantly between suppliers, even within the same country. Hence, using the generic database for the initial S-LCA screening is recommended and complementing the analysis with a ground-based study where real-world data can be collected to accurately assess the social impacts of the company suppliers and partners. The use of TD-ABC can also be limited when it

comes to modeling downstream stages, such as product use and end-of-life. Future studies can thus address this issue by extending the scope of TD-ABC or integrating it with complementary model.

IV.2 Discussion of The Case Study Results

The conducted assessment of packaging production allowed for comparing three different solutions: recycled paper-based, non-recycled, and plastic packaging produced by a company. It also allowed for performing a contribution analysis and exploring different manufacturing scenarios by varying their geographical locations.

Overall, results suggest that adopting a localized production can significantly reduce the social impacts of the different products. However, as this is not a feasible solution for most companies, strengthening supplier relationships can help introduce more sustainable practices within the supply chain. As discussed by (Reinales et al., 2020), the social impacts of the packaging sector are highly influenced by the supply chain actors; thus, considering a life cycle perspective is key for ensuring an effective shift towards more circular and sustainable business models. In this regard, certain activities, particularly those involving materials reuse, recycling processes, or product design for disassembly, could be oriented toward circular economy strategies. Embedding these principles into the production and sourcing decisions could amplify the social benefits observed.

This result calls for a more thorough investigation of the circular economy's role in improving companies' social performance while ensuring feasible and practical solutions. Future research could build on this by integrating circular economy metrics into ABC or TD-ABC frameworks. In particular, a collaborative study could explore how circular strategies affect both social and cost accounting outcomes in supply chains.

The results indicate that related social impacts are the most significant, notably for fair salary and trade unionism, highlighted by (Costa et al., 2022, 2019), who assessed paper and pulp production. The study also highlights the impacts related to corruption (value chain actors), mainly related to non-recycled paper production in the US.

The variability analysis performed on paper and paper-board production allowed us to identify the social risks associated with different geographical locations. Such analysis could greatly support companies to identify the social risks within their supply chain and thus identify areas of improvement. The quality of results should be ensured to enable a reliable decision-making process. In fact, companies might need to complement these results with a specific assessment to ensure no rebound effects on other social impacts.

It is important to highlight that the present study focused on a "cradle-to-gate" perimeter. Hence, this study does not account for the social impacts related to the use and end-of-life. Yıldız-Geyhan et al. (2017) show that packaging waste systems can be a significant source of social impacts linked to the presence of informal workers with bad working conditions and negative repercussions on the socio-economic development of the sector. In this regard, it is important to investigate these life cycle stages further in future studies.

V. Conclusion

With the on-going shift towards sustainable business models, companies are required to comprehensively assess and report the impacts of their value chain on the environment and society. This paper proposes an original approach for integrating Time-Driven Activity-Based Costing (TD-ABC) and Social Life Cycle Assessment (S-LCA) to fill this gap. Such framework allows for computing the social impacts associated with a company's activities and exploited resources by using a cost-accounting approach, which significantly facilitates the practical application of sustainability accounting.

This framework leverages accounting information at the organizational level to transition from a broad organizational perspective to detailed activity and product-level analysis, moving beyond traditional high-level assessments. By using the distribution or allocation factors defined by TD-ABC, it enables the allocation of costs and social impacts from resources to activities and ultimately to products.

An illustrative case study is conducted on a packaging company to showcase the features of the methodology that can be further adopted by future studies. The assessment covers a cradle-to-gate perimeter and is applied using a generic database (here PSILCA) for three different products: recycled paper-based packaging, non-recycled paper packaging and plastic packaging.

Results highlight that workers and local communities, and value chain actors are the most affected stakeholders in the packaging sector. The product with the higher share of social impacts is non-recycled paper packaging. The methods enabled the identification of the main social impacts (i.e. fair salary, public sector corruption and trade unionism), the main contributing unit processes (i.e. paper mills and paper board mills production in the USA) and activity (i.e. materials use). The inclusion of unused capacity analysis revealed inefficiencies across activities such as administration and machine usage, highlighting opportunities to optimize resource use and reduce associated social and economic impacts. From a managerial standpoint, this enables companies to balance cost-efficiency with social performance improvement opportunities. To help the company improve the social performance of its products, a variability analysis of the main contributing processes by varying the geographical location of the activities. The results emphasize the significant potential of the proposed methodology to

enhance sustainability accounting. By using specific data derived from TD-ABC, the methodology substantially improves the Social Life Cycle Inventory phase. Moreover, the methodology's compatibility with other input/output databases, such as Exiobase, further broadens its applicability.

A key research perspective for this study involves integrating the ABC-LCA methodology developed by Jourdaine et al. (2021) with our proposed methodology. This integration seeks to combine the strengths of both frameworks and databases (i.e., PSILCA and ecoinvent), creating a unified and harmonized methodology capable of analyzing environmental and social impacts within a single, cohesive framework, while also applying it to new case studies for broader validation and insights. However, this integration should be complemented by a strategic analysis to account for potential constraints posed by company partnerships and alliances, which may limit the feasibility of certain improvements. Future studies should explore these dynamics to further enhance the applicability of the model.

This study acknowledges certain limitations. The cradle-to-gate boundary of the model excludes the use and end-of-life stages, which are crucial for a full understanding of social assessments, particularly in the packaging sector where end of life management poses significant environmental and social risks. Including these stages would enable a more complete and meaningful evaluation. This limitation is inherent to the TD-ABC methodology, which focuses on internal processes and cost structures under managerial control. Future work could explore the integration of downstream-oriented models or develop complementary methods to cover post-manufacturing phases.

Additionally, relying on generic databases like PSILCA may lack specificity for some regions or processes. Enhancing data accuracy with grounded studies to collect primary data directly from stakeholders and suppliers would offer more practical, targeted insights. Despite these limitations, the proposed method TD-ABC-S-LCA framework provides a strong foundation for integrating social metrics into cost-accounting systems, helping companies to identify areas of improvements towards a more sustainable value chain and facilitate alignment with regulatory and reporting frameworks.

Looking ahead, several promising avenues could further extend the proposed framework for both academic research and business practice. In particular, the future of sustainability accounting may be shaped by the integration of Artificial Intelligence (AI), simulation capabilities, and extended supplier databases. Integrating AI into the TD-ABC-S-LCA model could significantly enhance its automation, scalability, and analytical power. AI tools could extract and structure time and cost data directly from enterprise systems (e.g., ERP), detect high-risk social hotspots in real time, and simulate alternative sourcing or production configurations. By relying on expanded supplier-level databases and dynamic simulation models, companies could better anticipate the impacts of operational decisions and policy

changes across global supply chains. Machine learning algorithms could also support predictive analytics by anticipating emerging social risks based on evolving supplier conditions or operational trends. This would reduce manual workload while enabling faster, data-driven sustainability decisions, an advancement of clear interest to practitioners managing complex supply chains. Furthermore, the model's compatibility with ERP systems and monetary databases like PSILCA or SHDB makes it adaptable and scalable. The optional reallocation of unused capacity impacts also provides a mechanism to internalize inefficiencies, reinforcing corporate accountability.

Finally, future research could explore embedding CSR indicators into the TD-ABC-S-LCA framework. This would allow for a more integrated approach to sustainability performance by linking operational data with CSR and ESG reporting standards. For businesses, such integration offers a concrete pathway to demonstrate how strategic commitments translate into measurable impacts. For the academic community, it opens up research on how accounting-based methodologies can bridge the gap between internal decision-making and external sustainability disclosures, thereby advancing the field of sustainability accounting and performance management. In addition, the TD-ABC-S-LCA framework offers strong potential for prospective analysis and future performance evaluation. By leveraging its time- and cost-based structure, companies can simulate future operational scenarios, test alternative sourcing strategies, and anticipate the social consequences of strategic decisions across activities and geographies. This enables forward-looking planning and proactive risk mitigation, supporting companies in aligning their operations with long-term sustainability goals and evolving stakeholder expectations.

6| Conclusion & Perspectives

This chapter summarizes the main contributions of the thesis, reflects on its limitations, and outlines future research perspectives. It revisits how the work addressed the integration of environmental and social impact data into procurement accounting and highlights the strategic, methodological, and operational implications for advancing corporate sustainability.

I. Research Trajectory and Fulfillment of Objectives

This thesis set out to answer a complex and timely research question:

How can businesses integrate accurate procurement-line level data - encompassing both environmental and social dimensions - into existing financial accounting frameworks to support corporate decarbonization, move beyond carbon-centric approaches, and enable holistic, data-driven sustainability decision-making?

The research was grounded in the recognition that indirect emissions, particularly those related to procurement, represent a critical yet underdeveloped frontier in corporate sustainability accounting. These upstream impacts are both environmentally and socially significant, but also methodologically difficult to quantify due to fragmented data, inconsistent reporting, and limited supplier transparency (Olanrewaju et al., 2025; Oliveira et al., 2022; Vieira et al., 2024). While much of the current focus is placed on carbon emissions, procurement decisions also influence a range of other environmental issues (e.g., water use, pollution, resource depletion) and social risks (e.g., labor rights violations, wage inequality, and corruption) (Hinterhuber and Khan, 2025). However, these broader sustainability dimensions are rarely integrated into corporate accounting frameworks in a way that supports operational decision-making or regulatory compliance (Comoli et al., 2023; de Souza Barbosa et al., 2023).

This thesis addresses that gap by advancing data-driven, automated, multidimensional models capable of capturing and aligning environmental and social impacts within procurement accounting systems. To address these challenges, the thesis was structured around four main research objectives:

Objective 1: To understand the state of the art in Scope 3 emissions accounting, with a focus on procurement-related practices and the integration of environmental and social impact data into corporate accounting systems.

A comprehensive analysis of existing environmental accounting frameworks, including LCA, EEIO

models, and hybrid methods—revealed a persistent trade-off between precision and completeness in current approaches. LCA enables detailed, high-resolution analysis at the product level but suffers from boundary truncation, limited scalability, and significant data gaps (Bjørn et al., 2018; Sonnemann and Margni, 2015). EEIO models, in contrast, offer comprehensive, economy-wide coverage but rely on aggregated sector averages that lack the granularity needed for procurement-level decisions (Nakamura, 2023; Suh, 2009).

These structural limitations are especially acute in the context of modern procurement functions, where data complexity is amplified by the diversity of suppliers, products, and formats (SBTi, 2023). Procurement records typically span thousands of items, with data ranging from structured ERP inputs to unstructured supplier documentation (Oliveira et al., 2022). This heterogeneity, coupled with inconsistent standards, classification schemes, outdated or mismatched emission factors, and non-standardized units (Vieira et al., 2024), creates major obstacles for accurate emissions accounting and integration into enterprise systems (El Haouat et al., 2023).

The review also revealed that most current practices underutilize supplier-specific data and rely heavily on proxies, resulting in highly aggregated and imprecise emissions profiles (Cimprich and Young, 2023; Finogenova et al., 2019; Ozawa-Meida et al., 2013; Paepe et al., 2023; Stridsland et al., 2023b). Crucially, none of the reviewed studies evaluate Scope 3 impacts using supplier-specific emission data at the procurement-line level, a precision threshold that is essential for operationalizing fact-based decision-making in purchasing. This gap significantly limits the ability of organizations to distinguish between suppliers based on real performance, and it prevents integration of emissions data into financial evaluations, supplier scoring systems, or procurement KPIs (Kaplan and Ramanna, 2021).

Moreover, the integration of environmental and social indicators into corporate accounting systems remains limited, both technically and conceptually. Although financial accounting systems are robust and auditable, they rarely interface with environmental or social metrics in a way that supports integrated sustainability decision-making (Comoli et al., 2023; Naro and Rambaud, 2023). As such, ESG factors remain siloed from core procurement and accounting processes, limiting their strategic utility and undermining corporate transparency and compliance with emerging regulations (Baehr et al., 2024).

Importantly, the review went beyond carbon to address broader environmental and social dimensions. The analysis underscored the growing role of Life Cycle Sustainability Assessment (LCSA), which combines environmental (e.g., GHG, water use), social (e.g., labor conditions, equity), and financial data to enable a more holistic view of procurement impacts (Valdivia and Sonnemann, 2024). However, methodological guidance and operational tools for implementing such multidimensional

assessments remain underdeveloped in the procurement context (Costa et al., 2019).

Together, these findings highlight an urgent need for a tiered, hybridized, and digitally supported framework, capable of dynamically selecting the most appropriate data type (monetary, physical, supplier-specific) for each procurement record while integrating ESG metrics into the broader architecture of corporate accounting systems (Anaya and Qutaishat, 2022; Ayinla et al., 2024; Eccles et al., 2014). This diagnostic phase establishes the foundation for designing a semi-automated, scalable model that supports not only robust carbon footprinting but also the alignment of environmental and social performance with financial decision-making, regulatory reporting, and supply chain innovation (de Souza Barbosa et al., 2023).

Objective 2: To identify the key challenges affecting the reliability of Scope 3 procurement-related accounting, analyze their interdependencies, and develop a strategic roadmap to improve accounting practices for greater accuracy and sustainability integration.

To achieve this, the research focused on diagnosing the systemic, methodological, and organizational obstacles that hinder the reliability and operationalization of Scope 3 procurement emissions accounting. To do so, a mixed-method approach was employed, combining a systematic literature review (Page et al., 2021), a qualitative analysis of a professional expert survey (Saldana, 2021), and a MICMAC structural analysis (Godet, 2007).

The findings from provided a robust conceptual and empirical map of the factors that degrade Scope 3 assessment reliability and create friction in sustainability accounting practices (Alzahmi et al., 2025; Baehr et al., 2024; Vieira et al., 2024). The core results were structured under the 6M framework (Gijo and Scaria, 2010), adapted from quality management and continuous improvement models:

- **Man**: Lack of expertise, limited training, and weak communication between procurement and sustainability functions often lead to data entry errors, poor coordination, and difficulties engaging suppliers in emissions reporting .
- **Method**: Inconsistent use of accounting standards and the widespread reliance on simplified spend-based methods result in aggregated estimates that fail to reflect actual supplier or product-level emissions, limiting precision and comparability.
- **Material**: Procurement data is frequently fragmented, incomplete, or poorly structured. Emission factors and supplier disclosures vary in quality, format, and granularity, making integration and validation challenging.
- **Machine**: Most procurement systems and ERPs are not equipped to process environmental data. Automation, real-time tracking, and AI-based matching tools are rarely used, limiting scalability and operational efficiency.

- **Measurement**: Data collection processes are inconsistent and lack verification. Many organizations struggle to align with regulatory standards such as the GHG Protocol or CSRD, especially when Scope 3 boundaries are unclear.
- **Management**: Governance structures are often weak, with sustainability goals disconnected from procurement KPIs. Resource constraints and limited transparency further hinder the integration of environmental performance into procurement strategies.

These systemic challenges are interdependent and self-reinforcing, meaning that progress in one area often depends on coordinated improvements in others.

The MICMAC analysis revealed several high-leverage factors that hold significant transformative potential for improving procurement-related emissions accounting (Godet, 2007). Among the most influential were the standardization of procurement emission factors and classification systems and regulatory alignment, which are essential to ensuring methodological consistency and enabling comparability across organizations and supply chains (Alvarez et al., 2014; Georgiou et al., 2019; Gómez et al., 2016; Rimano et al., 2021). The engagement of suppliers emerged as another pivotal element, particularly in fostering transparency and facilitating access to reliable, product-specific emissions data (Alejandrino et al., 2022; Lo-Iacono-Ferreira et al., 2017; Montoya-Torres et al., 2015). Closely related to this is the integration of environmental criteria into procurement performance management, which can reinforce accountability and incentivize sustainable decision-making.

The analysis also underscored persistent issues related to data quality, including gaps in completeness, lack of granularity, and inconsistencies in formatting or categorization (Baddley and Rasheed, 2023; Cucchi et al., 2023; Demeter et al., 2021; Forin et al., 2019, 2017). These weaknesses are exacerbated by limited automation, with many organizations lacking the infrastructure for real-time data tracking and digitalization of Scope 3 flows (Rodrigues, 2024; Uhlhorn et al., 2024). In parallel, insufficient internal expertise and training continues to hinder the ability of procurement teams to interpret, validate, and act upon environmental data effectively (Forin et al., 2019; Stridsland et al., 2023b). Finally, governance shortcomings, such as vague internal policies and a disconnect between sustainability and operational priorities, remain structural barriers to meaningful progress (Anthonissen et al., 2015; Cerutti et al., 2018; de Camargo et al., 2019; Kjaer et al., 2015; Yu et al., 2020). Addressing these interlinked variables is critical to advancing the integration of robust, data-driven sustainability practices in procurement functions.

Based on these results, the thesis developed a strategic roadmap using the Sustainability Balanced Scorecard (SBSC) framework (Figge et al., 2002; Kaplan and Norton, 1996), aligning sustainability performance with organizational strategy. The roadmap provides targeted recommendations across

different dimensions, offering actionable pathways for companies to improve data quality, decision-making, and climate accountability in procurement governance.

Objective 3.1: To develop a hybrid model that systematically integrates bottom-up and top-down approaches with supplier-specific, procurement and financial accounting data to address data gaps and enhance the accuracy of Scope 3 carbon and broader environmental impact accounting.

Based on the key challenges identified in the previous step, particularly those related to fragmented procurement data, the lack of supplier-specific emission information, inconsistent data structures, and the limited integration of digital tools, this thesis focused on developing a solution that could offer both methodological robustness and operational scalability.

To address these barriers, a Systematic Tiered Hybrid LCA (STHL) model was developed to support procurement-based emissions accounting by integrating the complementary strengths of traditional LCA and EEIO approaches (Suh et al., 2004). The model employs a tiered logic to select the most appropriate calculation method based on the type (monetary, physical, or supplier-specific), availability and quality of data. Designed for partial automation, it enables efficient data classification, matching, and calculation, making it scalable and applicable across large, heterogeneous procurement datasets, (Hagenaars et al., 2025).

The academic novelty of this approach lies in its automated decision tree architecture, minimizing manual intervention and ensuring methodological consistency at scale. The model supports emissions estimation at the procurement-line level, a level of precision not found in current academic literature (Cimprich et al., 2019; Finogenova et al., 2019; Keil, 2023; Paepe et al., 2023; Suh, 2009), and is specifically designed to handle the complexity of real-world procurement datasets. It also reconciles diverse and often fragmented procurement data in a harmonized and structured way, enabling users to integrate environmental metrics into standardized reporting workflows and procurement decision-making. This positions the model as both a methodological contribution and a practical tool for advancing Scope 3 management in complex organizational settings.

At the heart of this model is a six-tier hybridization logic, which is applied hierarchically and includes:

- Bottom-Up with Supplier-Specific Impact Factors, using verified or well-documented supplier-provided product-level emissions data such as PCFs or EPDs;
- Bottom-Up with Representative LCI Process Impact Factors, applied when physical quantities are available and can be matched to standard life cycle inventory (LCI) processes;
- Top-Down with Supplier-Level Monetary Intensity Factors, based on supplier-reported total GHG emissions and revenue to derive a custom intensity factor;

- Top-Down with Product-Level Monetary Intensity Factors, using EEIO intensities mapped to product classification codes (e.g., CPF Level 4);
- Top-Down with Sector-Level Monetary Intensity Factors, a fallback method applying average sector-level emission intensities; and
- Custom LCA for High-Impact Products, used for environmentally significant items lacking reliable data, where company-led modelling can approximate emissions based on partial supplier inputs.

This tiered architecture ensures that every procurement record can be assessed using the most specific and reliable method available, thereby improving both the completeness and reliability of Scope 3 emissions accounting.

Objective 3.2: To apply and evaluate the proposed hybrid model in an industrial context to assess its relevance, feasibility, and effectiveness for improving Scope 3 environmental impact accounting, and to explore its potential for supporting sustainability reporting, procurement decision-making, and sustainable innovation.

The model was applied and validated in collaboration with Eiffage, a leading French construction company, with a focus on the procurement of ready-mix concrete, one of the most emission-intensive and strategically important categories in the construction sector (Backes et al., 2023; Backes and Traverso, 2021). By combining financial data, physical quantities, product specifications, and emission factors from suppliers, national (BETie) and international databases, the model successfully delivered transparent and reliable carbon emission calculations.

The industrial case confirmed the model's adaptability and accuracy, while also revealing organizational and technical challenges related to supplier engagement, data standardization, and the limited automation of procurement platforms.

Overall, this hybrid model represents a scalable and replicable solution for companies aiming to strengthen Scope 3 emissions tracking. It enables fact-based procurement decisions, supports regulatory compliance, and lays the groundwork for integrating environmental accountability directly into purchasing workflows.

Conceptually, the model is designed to be extensible to other environmental impact categories as well as social risk indicators. However, the limited availability of supplier-level data beyond carbon emissions currently constrain the ability to test and apply the model across these broader dimensions in practice. As data disclosure standards evolve, this architecture offers a robust foundation for implementing more holistic, multi-impact sustainability assessments across complex supply chains.

Objective 4.1: To extend the top-down procurement accounting model by integrating social impact indicators, enabling a more holistic assessment and reporting of supply chain sustainability beyond carbon emissions.

While much of the focus in sustainability accounting has been placed on environmental indicators, particularly carbon emissions, this thesis recognizes that procurement decisions also carry significant social impacts (de Souza Barbosa et al., 2023).

To address this often-overlooked dimension, the research advances the automated top-down model by systematically incorporating social indicators into the procurement accounting framework, thereby aligning environmental and social assessments within a unified model. This contribution marks a significant methodological advance compared to other top-down studies, due to its automation and integration of the social dimension (Huang et al., 2009a; Lawson, 2024; Nicholls et al., 2015). It offers both conceptual clarity and practical tools to move sustainability accounting beyond carbon and toward a truly multidimensional assessment of procurement impacts.

The approach operationalizes social risk indicators using sector- and region-specific data derived from the PSILCA database, which quantifies social risks such as gender wage gap, and corruption (Maister et al., 2020). These metrics are translated into weighted impact values per monetary unit (Springer et al., 2025), thereby extending the top-down logic originally designed for environmental intensities in Chapter 4. Procurement line-items are classified using the same hierarchical logic (sectoral classification and spend mapping) applied to environmental data, ensuring semantic and structural consistency within the hybrid LCA model.

This integration not only reflects a more holistic vision of sustainability but also aligns the model with broader ESG disclosure requirements and the principles of Life Cycle Sustainability Assessment (LCSA) (Hinterhuber and Khan, 2025; Shan et al., 2020; Shekarian et al., 2022).

Objective 4.2: To explore how social impact indicators can be integrated into cost accounting systems, and evaluate the managerial relevance of this integration for procurement, supplier selection, and responsible sourcing.

To support strategic decision-making, these social indicators were further coupled with cost accounting tools, most notably Time-Driven Activity-Based Costing (TDABC) (Kaplan and Anderson, 2004). Building on the earlier integration of ABC and LCA by Jourdaine et al. (2021), this model extends that foundation by embedding the social dimension. This integration enables companies to assess trade-offs between financial efficiency and social responsibility by highlighting where low-cost sourcing may be linked to elevated social risks (Lehmann, 2023). By making social impacts visible and

comparable alongside carbon and financial data, the model offers a practical pathway for embedding multidimensional sustainability criteria into supplier evaluation, product selection, and procurement planning (Busse et al., 2016).

This expansion reflects a shift from narrow carbon accounting toward a more holistic LCSA approach, consistent with emerging standards and stakeholder expectations (Costa et al., 2019). It also equips companies with tools to align their procurement strategies with broader ESG goals and an evolving regulatory landscape (European Commission, 2024, 2023a). By integrating social and environmental metrics within a shared data infrastructure, this step addresses the fragmentation of sustainability information that has long hindered responsible purchasing (ISO 20400, 2017).

Collectively, these contributions provide a replicable and operational model for embedding multidimensional sustainability into procurement practices. However, the implementation of such an approach is not without limitations, which are explored in the following section.

II. Theoretical and Practical Limitations

To provide a structured and analytically grounded view of the challenges encountered, the limitations are presented through five interrelated dimensions: epistemological limitations, methodological limitations, operational and practical constraints, institutional and organizational barriers, and futurity and strategic relevance limitations.

This structure reflects both theoretical tensions and real-world implementation challenges encountered during the model's development and application.

II.1 Epistemological Limitations

While the hybrid environmental accounting model developed in this thesis represents a significant methodological and operational advancement, its implementation has revealed several limitations and constraints. Compared to existing hybrid methodologies, which often operate at aggregated levels using proxies, generalized assumptions or high-level spend categories (Baddley and Rasheed, 2023; Cimprich and Young, 2023; Finogenova et al., 2019; Keil, 2023; Paepe et al., 2023), the model presented here distinguishes itself by integrating supplier-specific data directly at the procurement line-item level. This level of granularity allows for more accurate, product-specific emissions attribution and represents a substantial improvement over traditional spend-based or sector-average approaches (Nakamura, 2023; Suh, 2009). However, this increased resolution significantly raises the model's dependency on high-quality, structured, and verifiable supplier data, resources that are often unavailable, inconsistent, or difficult to verify (Ciroth, 2021; Olanrewaju et al., 2025).

A core limitation encountered during the application of the hybrid model was the restricted availability

of supplier-specific data. The supplier-level pathway of the hybrid pipeline, designed to provide the most accurate and granular calculations, was applied exclusively to ready-mix concrete, as it was the only category for which detailed and structured product formulations and environmental declarations were accessible. Other procurement categories, such as steel, or bitumen, lacked the necessary technical detail, physical data, or environmental disclosures to enable bottom-up modeling. As a result, these categories had to rely on less accurate tiers, such as top-down EEIO-based proxies or sectoral LCI averages, limiting the resolution and decision-relevance of the results (Crawford et al., 2018).

In the case study, supplier-specific data were available only for carbon emissions, which limited the practical application of the model to broader impact categories such as water use, toxicity, or social risks, even though the model architecture is designed to be generalizable across multiple sustainability dimensions. This reflects a wider challenge in practice, where companies continue to struggle to move beyond carbon and to systematically account for broader environmental and social impacts in procurement decisions (Fraser et al., 2020; Patil et al., 2022).

Even in cases where supplier-specific carbon data was available, verifying the environmental information provided by suppliers posed a critical challenge (Oliveira et al., 2022). The thesis revealed that, in the absence of formal data disclosure protocols or third-party verification mechanisms, it is nearly impossible to assess the credibility and consistency of supplier-declared emission factors. Discrepancies in reporting formats, unclear system boundaries (e.g., inclusion of transport or VAT), and inconsistent units severely restrict the comparability and auditability of supplier-specific inputs (Busse et al., 2016; Diebel et al., 2024). This lack of standardized data and verification protocols undermines trust in data and reduces the auditability of supplier-derived values.

A further limitation concerns the use of the PSILCA database for modeling social risks, particularly the transparency and subjectivity of its weighting methods. While PSILCA provides a practical framework for integrating social indicators into procurement analysis, its results are derived from expert-based scoring and normalization schemes rather than directly measured impacts (Pollok et al., 2021). This introduces interpretive uncertainty and may affect comparability across contexts. The lack of full transparency in how social risks are weighted and aggregated limits the auditability and stakeholder acceptance of the results, especially as new regulations increasingly demand methodological clarity and traceability (Kokubo Roche et al., 2025).

II.2 Methodological Limitations

Another major constraint relates to the integration of multiple, heterogeneous data sources, monetary, physical, and supplier-specific (Crawford et al., 2018; Jiang et al., 2014). While the model is designed to be tiered and adaptive, integrating these sources is not without methodological or

operational complications. Differences in system boundaries, temporal coverage, and allocation rules can lead to internal inconsistencies within the dataset (Joshi, 1999; Wiedmann et al., 2011). For instance, sector-level EEIO data may reflect outdated economic structures, while supplier-specific emissions factors may be based on different geographic contexts or emission scopes. Mapping procurement records to environmental databases often requires a high degree of manual intervention, especially when product labels are vague, incomplete, or company-specific (Herth and Blok, 2023; Ozawa-Meida et al., 2013). These issues reduce automation potential and increase the risk of subjective interpretation.

From a methodological perspective, inconsistencies across existing sustainability accounting frameworks (e.g., GHG Protocol, OLCA, ISO 14067) further complicate implementation. These frameworks vary significantly in their definitions of hybrid modeling, system boundaries, and data collection strategies, leading to divergent interpretations and practices (Weidema, 2022), as outlined in Section 2.B.IV. The EEIO approach, while scalable, assumes homogeneity within sectors. Conversely, LCI-based modeling is more precise but requires data granularity that is rarely available at scale. Integrating these fundamentally different approaches within a single tiered model introduces methodological tension, especially when results are used for compliance, investment analysis, or public reporting (Strømman et al., 2009).

A specific limitation of the current model lies in its reduced applicability to services and subcontracted activities, which are inherently more fragmented and difficult to quantify than material purchases. Unlike goods, services often lack physical quantities, standardized emission factors, or structured documentation (Huang et al., 2009b). Subcontracted work, common in sectors like construction or maintenance, is typically bundled under aggregated invoices or project codes, making it challenging to isolate emissions by activity or supplier (Le Den et al., 2022). This prevents the model from achieving the same resolution or reliability for indirect procurement flows.

II.3 Operational and Practical Constraints

The practical feasibility of deploying the hybrid model is significantly constrained by infrastructure gaps, low automation readiness, and limited system compatibility. The model's effective functioning depends on access to standardized and structured procurement data, which is rarely available in most enterprise environments (Chen et al., 2021; Stenzel and Waichman, 2023). Common systems such as ERP or PDM platforms are primarily designed to support financial transactions and generally lack the technical capacity to store environmental metadata or perform unit-aware sustainability analyses (Alzahmi et al., 2025; Anaya and Qutaishat, 2022).

In practice, procurement platforms rarely include essential sustainability-related data, such as

standardized product codes (e.g., CPF), physical quantities, or embedded emissions attributes. This forces organizations to engage in labor-intensive data preprocessing before emissions can be accurately calculated (Schöpper and Kersten, 2021). Even when advanced techniques such as Natural Language Processing and semantic classification are applied, the vagueness of product descriptions and inconsistencies in supplier taxonomies limit the effectiveness of automation and severely restrict scalability (Ayadi et al., 2020; Blanchy et al., 2023; Lee, 2025). For example, in the concrete case study, mix formulations were often captured in unstructured formats and had to be harmonized using rule-based scripts and a dynamic terminology dictionary, processes that are resource-intensive and not easily transferable without structural changes in underlying systems. Moreover, the misalignment between financial and sustainability data structures complicates integration. Emission estimation often requires mapping between procurement categories, cost codes, and impact classifications, which are rarely harmonized across systems (Rodrigues, 2024). This fragmentation increases the burden of manual reconciliation and limits the potential for automation or seamless reporting.

From a conceptual standpoint, integrating the hybrid model with cost accounting frameworks such as Activity-Based Costing (ABC) or Time-Driven ABC (TDABC) presents a promising avenue for aligning environmental impacts with financial performance. This is supported by prior research demonstrating successful integration of LCA with ABC (Jourdaine et al., 2021) and SLCA with TDABC (Essouid et al., 2024). However, in practice, these advanced cost accounting frameworks remain largely confined to academic literature (Afonso and Paisana, 2009; Siguenza-guzman et al., 2013). Their adoption at the company level is limited due to the lack of interoperability with operational systems, and the absence of regulatory incentives that would mandate or encourage such integration (Kenton, 2024).

These infrastructure and data readiness constraints make it difficult to scale the model across large and diverse procurement portfolios without significant investments in data engineering, digital tooling, and cross-system integration capacity (Uhlhorn et al., 2024).

II.4 Institutional and Organizational Barriers

Beyond technical constraints, several institutional and organizational factors further hinder the effective implementation of the integrated sustainability accounting model. One of the most significant barriers lies in the misalignment of strategic priorities: procurement teams are rarely incentivized to consider environmental and social performance, as their key performance indicators (KPIs) continue to focus primarily on cost, quality, and delivery timelines (Hinterhuber and Khan, 2025). As a result, sustainability accounting is often perceived as a peripheral compliance task rather than a core procurement responsibility, leading to low engagement and limited cross-functional collaboration.

Governance structures and internal expertise present additional challenges. Sustainability data management is typically siloed from core operational functions such as procurement, finance, or supply chain management (Smaldone et al., 2025). In many organizations, there is a lack of clearly defined ownership of sustainability data, and procurement or finance staff often lack the training needed to assess the quality, system boundaries, or relevance of environmental information received from suppliers. This gap in internal capabilities compromises the reliability of data inputs and weakens the credibility of downstream emissions estimates (Akella et al., 2024).

At the supply chain level, supplier engagement remains largely informal and voluntary. Most organizations do not include contractual obligations for suppliers to disclose emissions data or provide EPDs. This best-effort approach results in inconsistent participation and limits the availability of verified, product-specific data (Patil et al., 2022). The problem is particularly acute among small and medium-sized enterprises (SMEs), which often lack the tools, resources, or reporting maturity to provide high-quality environmental disclosures, thus weakening the effectiveness of supplier-specific tiers in the model (Bergerson et al., 2020).

II.5 Futurity and Strategic Relevance Limitations

A critical operational limitation of current sustainability accounting models lies in their inability to support dynamic or frequently updated datasets (Oliveira et al., 2025). In practice, most enterprise systems do not facilitate the automated ingestion, synchronization, or recalculation of updated supplier data, emission factors, or classification codes. As a result, model outputs can become quickly outdated, particularly in fast-evolving sectors such as construction, manufacturing, or transportation, where upstream disclosures and emission factors are frequently revised (Paolone et al., 2020). The lack of mechanisms for real-time or periodic data refresh restricts the model's responsiveness and reduces its strategic value for continuous improvement, internal decision-making, and external reporting (Pizzi et al., 2024). Maintaining accuracy over time thus requires repeated manual updates and data reconciliation, efforts that are resource-intensive and limit the model's scalability across large or diverse procurement systems.

Additionally, the use of outdated or geographically misaligned emission factors introduces further credibility risks, particularly in top-down modeling tiers. Many widely used EEIO databases are built on economic and environmental data that is more than a decade old and tied to foreign currencies or national contexts that do not reflect local conditions (Nakamura, 2023). While inflation and exchange rate adjustments can be applied, such corrections cannot fully account for changes in production technologies, energy mixes, or policy environments, resulting in potentially significant deviations between modeled and actual emissions (Bartoli et al., 2019).

More fundamentally, the hybrid model is currently constrained in its ability to support forward-looking or scenario-based analysis. Strategic procurement decisions, such as aligning sourcing strategies with 2030 decarbonization targets or simulating climate policy impacts, require prospective modeling capabilities that are not yet supported (Rodrigues et al., 2024). Most data sources used in the model, including ecoinvent and EEIO databases, are static and retrospective, capturing historical averages rather than dynamic projections (Oberschelp et al., 2023). This lack of future-oriented datasets or prospective LCA features limits the model's applicability for organizations seeking to align procurement strategies with emerging frameworks such as the Science-Based Targets initiative (SBTi), which require forward-looking assessments of decarbonization pathways and long-term impact projections. Without a shift toward dynamic, forward-compatible data structures, the model's strategic relevance remains tied to retrospective analysis rather than proactive, long-term sustainability planning.

III. Future Research Directions and Perspectives

Building on the development of a flexible hybrid model for procurement-based sustainability accounting at varying levels of data granularity, this thesis opens several key avenues for future exploration. These perspectives are organized using the same five categories as the limitations section; epistemological, methodological, operational and practical, institutional and organizational, and futurity and strategic relevance, to ensure consistency.

III.1 Epistemological Perspectives

From an epistemological perspective, applying the model to a broader range of procurement categories raises important questions about the assumptions behind emissions accounting. Each sector has different ways of buying goods, collecting data, and measuring environmental impact. As a result, the model must adapt to these differences, which challenges what can realistically be known, measured, and standardized across various contexts.

A first and immediate direction concerns the expansion of the supplier-specific model to other procurement categories. While the model was tested primarily on ready-mix concrete, future applications should investigate its adaptability to other procurement categories such as steel, and bitumen. These categories differ in data structures, supplier engagement levels, and environmental impact profiles. Comparative case studies could examine the applicability of tier logic across product families, highlighting where supplier-specific or physical modeling yields the greatest accuracy, and where monetary proxies remain the only viable approach.

Another key challenge lies in the verification and validation of data provided by suppliers. As the model increasingly relies on supplier-specific disclosures, questions arise about the reliability, consistency,

and truthfulness of such information. Future research could develop frameworks to assess data trustworthiness, including third-party verification protocols, audit mechanisms, and confidence scoring systems. These tools are not only technical enablers but epistemological safeguards, ensuring that what is reported can be reasonably accepted as true, especially in high-impact procurement categories.

Institutionalizing supplier reporting using standardized digital templates could further support consistent data collection practices and create conditions for routine validation at scale. The integration of technologies such as blockchain or distributed ledgers may also enhance traceability and prevent data manipulation, particularly in decentralized supply chains.

Closely related is the potential of real-time data collection and monitoring. Traditional emissions reporting relies on retrospective, static datasets that may be outdated or incomplete. By contrast, real-time monitoring systems, integrated into procurement workflows, could provide continuous, dynamic insight into ESG performance. Future work may explore how Internet of Things (IoT) devices, digital product passports, or automated supplier reporting interfaces can contribute to a more immediate and context-aware understanding of impacts. Such developments would significantly enhance the temporal validity and situational relevance of environmental data in decision-making.

III.2 Methodological Perspectives

Methodological innovation is essential to ensure that the hybrid accounting model remains analytically rigorous, scalable across sectors, and aligned with evolving standards of transparency and decision-making under uncertainty.

One pressing methodological challenge concerns the modeling of services and subcontracted activities, which are often characterized by fragmented value chains and limited physical data. Unlike goods, services such as consulting or maintenance rarely come with emissions information, and subcontracted work is often billed under aggregated cost codes. This makes emissions attribution complex and imprecise. New approaches could include the integration of labor-based or time-based proxies (e.g., through Time-Driven Activity-Based Costing), as well as the development of structured reporting templates for subcontractors to disclose activity-specific environmental data.

Building on this, further methodological development is needed to formalize how uncertainty is managed across the hybrid model. This includes the validation of assumptions and the structured selection of proxies. The use of Monte Carlo simulations, statistical modeling, or probabilistic tiers could help contextualize outcomes and inform risk-adjusted procurement decisions.

Closely related is the need to conduct tier sensitivity analysis and scenario testing. Future work could

quantitatively assess the differences in emission estimates across the six tiers of the hybrid model. Sensitivity testing under various assumptions (e.g., unit prices, transport distances, emission factors) would allow researchers to identify high-risk uncertainty zones and assess the robustness of procurement decisions. Scenario modeling could further simulate the impacts of regulation changes, supplier decarbonization trajectories, or shifts in procurement strategy, thus positioning the hybrid model as a strategic planning tool.

Finally, to ensure methodological credibility and support external comparability, it would be valuable for future research to prioritize alignment with emerging standards and frameworks. References such as GHG Protocolc, the Organizational Life Cycle Assessment (OLCA) framework, and related methodologies can provide common ground for hybrid model refinement, increasing both robustness and legitimacy in regulatory or ESG reporting contexts.

III.3 Operational and Practical Perspectives

Future investigations may consider exploring mechanisms to institutionalize supplier reporting using standard digital templates and integrate them directly into procurement platforms. Advanced verification protocols, such as blockchain or distributed ledgers, could ensure data traceability and guard against manipulation, particularly for high-impact inputs. These technologies could also support alignment with initiatives like PACT (Partnership for Carbon Transparency), enabling real-time and cross-organization emissions tracking.

A promising and necessary perspective involves the transformation of ERP and procurement systems into sustainability-aware platforms. Currently, most enterprise systems are optimized for financial transactions and are structurally unable to store environmental metadata, track unit-aware quantities, or retrieve EPDs. Future work should explore the co-development of ERP extensions capable of processing carbon, water, and social impact fields. These systems should also integrate with sustainability APIs and digital product passports, enabling seamless linkage between procurement records and environmental disclosures. This digital integration is not simply a technical upgrade, it represents a structural evolution in how sustainability is operationalized at scale.

Operationalizing this model at scale demands seamless digital integration. The current disconnect between sustainability data and ERP systems remains a critical barrier. Future research could also examine how low-code or no-code platforms (e.g., Power BI) might democratize sustainability analytics, allowing procurement professionals to generate visual dashboards, alerts, or decision-support tools without specialist support.

Equally important is the extension of the hybrid model to multidimensional impacts, beyond carbon alone. Future studies should incorporate regionally sensitive indicators such as water use, biodiversity

loss, and land occupation, particularly relevant in sectors like construction, agriculture, and textiles. This would require integrating more granular LCI databases or supplier-specific disclosures that go beyond climate impacts, supporting a shift toward Life Cycle Sustainability Assessment frameworks and compliance with upcoming CSRD multi-indicator reporting requirements.

To ensure the quality of supplier data integrated into the model, future research should design and implement a data scoring framework. Such a framework would assess each supplier declaration based on transparency, completeness, geographic and temporal alignment, and methodological consistency. Data scoring systems could be built directly into procurement workflows, with high-quality submissions accepted automatically, and low-scoring data flagged for further verification or replaced with conservative proxies. This would strengthen trust in supplier data and reduce manual validation burdens.

III.4 Institutional and Organizational Perspectives

At the institutional level, future research is encouraged to explore how to strengthen supplier capacity for sustainability reporting, particularly among SMEs with limited sustainability expertise. This may involve developing open-access tools, regional support hubs, and sectoral training programs to ensure broader participation and consistent data quality across supply chains.

To move beyond voluntary disclosure, research could investigate how environmental reporting can be embedded contractually, through standardized templates, onboarding protocols, and procurement portals. Incentive-based mechanisms, such as preferential tender scoring or contract extensions, may further motivate high-quality supplier disclosures.

Improving internal governance is also critical. Studies might examine how sustainability indicators can be formally integrated into procurement KPIs, supplier scorecards, and performance reviews. Aligning incentives, through dual KPIs or revised bonus structures, could better synchronize procurement priorities with environmental goals.

Cross-functional coordination remains a barrier. Future work may explore data governance models that promote interoperability between procurement, finance, and sustainability teams. This could include shared metadata standards, data stewards, or cross-departmental governance boards to reduce fragmentation and ensure accountability.

Finally, many organizations lack the internal expertise to operationalize sustainability in procurement. Future research could assess how targeted capacity-building, such as training programs, procurement-specific sustainability curricula, or the creation of “green buyer” roles, affects implementation outcomes and long-term adoption.

III.5 Futurity and Strategic Relevance Perspectives

The long-term relevance of hybrid Scope 3 accounting models depends on their ability to support forward-looking decision-making, adapt to evolving regulatory environments, and remain responsive to dynamic supply chain conditions. To fulfill this role, future research must extend beyond retrospective analysis and engage with scenario planning, predictive modeling, and system resilience.

An important direction involves enhancing the model's temporal responsiveness. While earlier perspectives have addressed real-time supplier data collection, future work could investigate how enterprise systems, such as ERP, can support the periodic refresh of key environmental and social inputs; such as emission factors, supplier classifications, or disclosure updates, through automated data pipelines. This would reduce dependency on manual updates and enable continuous improvement, especially in fast-changing sectors like construction or manufacturing.

In parallel, efforts are needed to improve the regional and temporal precision of emission factors used in hybrid modeling. Many widely used EEIO datasets are outdated and geographically misaligned. Future research could explore the development of dynamically adjusted or region-specific databases that reflect current production practices, energy mixes, and regulatory contexts. These localized datasets would improve the accuracy and credibility of emissions estimates, particularly in top-down modeling tiers.

Equally critical is the need to embed scenario modeling capabilities into the hybrid framework. Strategic procurement planning; such as aligning sourcing with long-term decarbonization goals or assessing the impact of future carbon pricing, requires tools that can simulate alternative futures. Future research may consider integrating prospective LCA datasets, policy-linked variables, or science-based targets to enable organizations to assess long-term outcomes and risks.

From an organizational learning perspective, longitudinal studies could help assess how the hybrid model is implemented over time. Tracking changes in procurement practices, data quality, and emissions performance across multiple time points would generate empirical insights into the model's transformative potential, beyond static emissions reporting.

To support long-term alignment with regulatory and ESG disclosure frameworks, future work could also contribute to the harmonization of sustainability standards, reporting frameworks and regulations. Aligning definitions, methodologies, and reporting formats across initiatives such as the GHG Protocol, ISO 14067, OLCA, the EU Taxonomy, and the CSRD would improve data comparability, reduce reporting burdens, and ensure consistency between procurement data and broader sustainability disclosures.

Finally, future research may consider adopting a strategic foresight lens. Anticipating shifts in regulation, market expectations, and climate risk will be essential to designing procurement systems that are not only compliant but resilient and adaptive. Hybrid models must evolve into forward-compatible infrastructures, capable of informing not just emissions tracking, but long-term procurement strategy under uncertainty.

In closing, this thesis is more than the outcome of a research journey, it is a testament to a growing awareness that the choices we make behind spreadsheets, purchase orders, and procurement codes ripple far beyond company walls. It is a reminder that even in the most operational corners of a business lies immense potential to shape a more sustainable, just, and resilient world. The work undertaken here began as a technical challenge, but it evolved into something deeper: a search for coherence in a fragmented system, for truth in data, and for accountability in places often left unexamined. It is a call to rethink not only how we account for emissions, but how we assign responsibility, build trust with suppliers, and embed sustainability not as a siloed initiative, but as a shared language across the entire value chain. In an era where sustainability ambition too often outruns execution, this thesis affirms that with the right tools, structures, and collective will, procurement can move from the margins to the forefront of corporate transformation.

Appendices

Appendix 2-1. Literature Review Methodology and Results Overview

Due to the size and formatting requirements of the review matrix, this appendix is provided as an external document for readability. It includes the full search strategy, screening criteria, list of all retrieved articles, and the matrix of 44 included studies covering over 54 case studies.

Access the full appendix here:

https://docs.google.com/spreadsheets/d/1SwIhRzS1Q23M_sEfoFt6SVHp6zVZSiHI/edit?usp=sharing&ouid=101764286973883338185&rtpof=true&sd=true

Appendix 3-1. Survey Questionnaire: Structure and Content

Title : Expert Survey on Reliability Factors for Scope 3 Emission Data in Procurement

1. Description

The objective of this survey is to identify key factors that influence the reliability of Scope 3 emission data related to procurement. Your expertise is essential in guiding these findings, and your insights are valuable for refining our understanding and improving data reliability in emission reporting.

2. Background Information

O. Name

O. Position/Role

O. Field of Expertise

C. Years of Experience (0 – 2 years, 2 – 5 years, 5 – 10 years, more than 10 years)

3. Factors Influencing Scope 3 Reliability

O. Man (Human Factors) : What human-related challenges impact the reliability of Scope 3 emission data? Please specify any obstacles related to human factors and suggest areas where additional support or resources could enhance data accuracy.

O. Methods (Calculation Methodologies) : What specific challenges do you encounter with calculation methodologies for Scope 3 emissions? Please describe any methodological issues that impact data reliability and suggest potential areas for improvement.

O. Materials (Data Quality and Type) : How do the quality and type of data used for Scope 3 emissions influence reliability? Please highlight any specific challenges you've identified and suggest improvements to enhance data reliability.

O. Machines (Technological Tools and Systems) : What technological constraints do you encounter when managing or analyzing Scope 3 emission data? Please describe how these challenges impact data accuracy and reliability, and suggest any improvements.

O. Measurement (Standards and Processes) : What challenges do you encounter in the standards and processes used for measuring and reporting emissions? Please specify any areas where improvements are needed to enhance reliability.

O. Management : How do organizational practices and policies affect the reliability of Scope 3 emission data? Please describe any management-related obstacles and suggest ways that organizational changes could improve data accuracy and reliability.

4. Rating

For each factor below, please rate its impact on Scope 3 emission data reliability (1 - very low to 5 - very high); Man, Method, Material, Machine, Measurement, Management

5. Additional Comments

Additional Comments: Please share any other insights or suggestions that could contribute to understanding and enhancing the reliability of Scope 3 emissions data in procurement.

Appendix 3-2. Full description of the challenges identified

6M Category	Code	Challenges	Description
MAN	**C01**	Communication and Data Sharing	Miscommunication and data-sharing gaps between suppliers, procurement, and sustainability teams weaken data reliability. Lack of clear responsibilities, reluctance to share data, and misalignment between departments lead to inconsistent and incomplete information. The absence of centralized data-sharing platforms further complicates reporting.
	C02	Supplier Readiness, Trust, and Cooperation	Supplier engagement in carbon emissions calculation is hindered by lack of expertise, trust issues, and reluctance to share data. Many suppliers, especially SMEs, struggle with reporting due to limited knowledge and complex requirements. Concerns over confidentiality and business risks further reduce data transparency.
	C03	Expertise, Training, Knowledge Gaps and Understanding	Limited expertise, lack of training, and knowledge gaps hinder emissions tracking, calculations and reporting. Many procurement teams and supply chain operators lack standardized training in carbon accounting and Scope 3 emissions, leading to data inconsistencies and compliance challenges. High staff turnover further exacerbates knowledge retention issues.
	C04	Manual Data Entry and Matching, and Human Errors	Reliance on manual data entry and handling introduces significant accuracy risks in emissions calculation. Frequent human errors, reliance on spreadsheets, and manual adjustments and matching foreground data with background data lead to inconsistencies, impacting data reliability. Unit conversion mistakes, input errors, and the need for manual corrections further increase the risk of inaccuracies.
METHOD	**C05**	Inconsistent Supplier Methodologies	Discrepancies in emissions data arise as different suppliers employ varying carbon accounting and tracking methods and emissions factors. This lack of consistency in methodologies leads to challenges in ensuring reliable and comparable data across the supply chain, affecting the overall accuracy of emissions calculations.
	C06	Methodologies and Emissions Calculations	Complex emissions calculations face challenges due to factors like empty miles, fuel mix variations, and diverse value chains. Current methodologies often fail to account for these complexities, leading to inaccuracies. Small suppliers also struggle with the complex reporting requirements, further complicating emissions tracking and calculation.
	C07	Data Aggregation from the Use of the Spend-Based Approach	Spend-based emissions estimation methods rely on broad, industry-average emission factors, leading to low granularity and reduced accuracy. While spend-based approaches are widely used due to their simplicity, they fail to capture supplier-specific variations and often result in discrepancies when compared to activity-based approaches. Many companies over-rely on spend-based data, despite its lack of precision and representativeness.

MATERIAL	**C08**	Supplier Data Quality and Consistency		Supplier data on emissions is often incomplete, outdated, or inconsistent, which hinders accurate emissions reporting and decision-making. Many suppliers provide generic or high-level estimates instead of specific or measured data, leading to over-reliance on industry averages or inaccurate assumptions. Data gaps and discrepancies across suppliers further complicate comparisons and integration of emissions data into procurement processes.
	C09	Challenges in Data	Data Completeness and Gaps	Data gaps, missing information, and incomplete datasets hinder accurate emissions calculations. These gaps create inconsistencies in reporting, making comparisons difficult and reducing the reliability of emissions data. Variability in data collection and lack of comprehensive data further complicate the integration of emissions data into procurement processes.
			Data Consistency	Inconsistent data structures, formats, and sources reduce the reliability of emissions data. Variations in data handling and reporting lead to discrepancies that undermine the accuracy of calculations and hinder comparisons, complicating decision-making and regulatory compliance.
			Data Granularity	Low data granularity limits the accuracy and relevance of emissions calculations. his lack of granularity hinders precise impact assessments and decision-making, reducing the effectiveness of carbon reduction strategies.
			Data Quality and Precision	Insufficient data quality assessments, unreliable data sources, and lack of precision in data collection lead to significant challenges in emissions reporting. The absence of clear data origin and limitations further impacts the accuracy of results and decision-making.
			Use of Outdated Data	The use of outdated significantly compromises the accuracy and reliability of emissions calculations. Many emissions models, including Scope 3 calculations, rely on old assumptions or outdated records, leading to inconsistencies and poor decision-making. This reliance on outdated information weakens the quality of emissions tracking, reduces comparability across datasets, and impacts compliance efforts.
MACHINE	**C10**	Procurement Platform Integration for Carbon Accounting		Procurement platforms lack seamless integration with emissions tracking, sustainability databases, and financial systems, creating data silos and inefficiencies. Many procurement tools do not support automated carbon tracking, fail to collect emissions data directly, and struggle to integrate with sustainability and reporting software. These limitations hinder data accuracy, decision-making, and cross-functional collaboration.
	C11*	Automation, AI, and Real-Time Data Tracking		Limited automation, AI integration, and real-time tracking create inefficiencies in emissions calculation. Many procurement platforms lack automated data collection, leading to manual input, delays, and inconsistencies. The absence of AI-driven tools and real-time synchronization further weakens data reliability.

	C12*	Software Capabilities for Emissions Data Processing	Outdated, inadequate, and limited software capabilities hinder the efficient processing of emissions data. Many software and tools struggle with large datasets and complex emissions calculations, leading to slow analysis and reduced accuracy. Additionally, existing tools are not mature enough to handle evolving emissions tracking requirements.
MEASUREMENT	**C13**	Data Collection	Incomplete, inconsistent, and unstructured data collection weakens data reliability and integration into procurement processes. Variability in data identification and lack of leadership emphasis further contribute to gaps in emissions data collection.
	C14	Data Verification	Lack of third-party validation and verification of supplier-specific data undermine emissions calculation accuracy. Many companies manipulate calculations or provide unverifiable data, increasing the risk of greenwashing. Varied reporting frameworks and difficulties in verifying supplier disclosures create gaps in data reliability.
	C15	Standardization and Regulatory Alignment	Inconsistent reporting standards, sector-specific methodologies, and regional regulatory differences create data discrepancies and hinder comparability. Conflicting emissions frameworks, varied calculation models, and non-harmonized approaches complicate compliance and benchmarking.
MANAGEMENT	**C16**	Weak Governance and Unclear Policies	Weak governance structures and unclear corporate policies undermine the reliability, consistency, and prioritization of emissions tracking. Many companies lack structured governance policies, leading to variability in carbon data management, policy gaps, and enforcement challenges. Additionally, large corporations often impose one-size-fits-all sustainability policies, which may not be feasible for SMEs.
	C17	Cost, Time, and Resource Constraints	High costs, time constraints, and limited capacity hinder emissions tracking. SMEs struggle to afford advanced tools, while procurement teams lack time and resources for detailed reporting. Expensive software and labor-intensive LCA studies further slow adoption.
	C18*	Aligning Procurement with Sustainability Goals	Procurement strategies often prioritize cost and supply chain efficiency over sustainability, leading to weak integration of emissions tracking and environmental goals. Many procurement policies lack clear mandates for sustainability, and emissions tracking is often excluded from key performance indicators (KPIs). Additionally, procurement teams struggle with competing priorities, unclear accountability, and a lack of incentives to incorporate Scope 3 reporting.
	C19*	Transparency	Lack of transparency and limited disclosure affect data clarity and reliability. Inconsistent transparency in reporting weakens trust and makes accurate assessments difficult.

Appendix 3-3. Calculation of weighting factors

To reflect the level of professional experience of respondents, we applied a weighting factor based on the average years of experience within each category. The average was calculated as the midpoint between the minimum and maximum years of experience. For the category "More than 10 years", the maximum was assumed to be 30 years, resulting in an average of 20 years.

Experience range	Minimum experience	Maximum experience	Weighting factor
0 – 2 years	0	2	1
2 – 5 years	2	5	3.5
5 – 10 years	5	10	7.5
> 10 years	10	30	20

Each rating given by the respondents was then multiplied by the corresponding weighting factor to account for the influence of experience on the perceived importance of each challenge. This weighting approach allows for a more nuanced analysis of how experience may shape this evaluation ($rw_{i,m} = r_{i,m} \times w_i$). The codes M1 to M6 represent the six categories of the 6M framework as follows: M1 – Man, M2 – Method, M3 – Material, M4 – Machine, M5 – Measurement, and M6 – Management.

Experience range (e)	Weighting Factor (w)	Interview (i)		Responses (r)						Responses x Weighting Factor (rw)					
				M1	M2	M3	M4	M4	M6	M1	M2	M3	M4	M5	M6
0 - 2 years	1	I 2	3	4	5	5	3	5	5	4	5	5	3	5	5
		I 4		5	4	4	2	3	2	5	4	4	2	3	2
		I 5		3	2	4	4	4	4	3	2	4	4	4	4
2 - 5 years	3.5	I 3	5	5	5	5	2	5	4	17.5	17.5	17.5	7	17.5	14
		I 7		3	5	4	3	4	3	10.5	17.5	14	10.5	14	10.5
		I 19		4	5	5	4	5	4	14	17.5	17.5	14	17.5	14
		I 20		3	4	5	4	5	3	10.5	14	17.5	14	17.5	10.5
		I 34		3	4	5	5	4	3	10.5	14	17.5	17.5	14	10.5
5 - 10 years	7.5	I 1	17	4	5	5	4	5	4	30	37.5	37.5	30	37.5	30
		I 6		4	5	5	4	5	4	30	37.5	37.5	30	37.5	30
		I 9		2	3	5	4	4	5	15	22.5	37.5	30	30	37.5
		I 10		4	5	5	4	5	5	30	37.5	37.5	30	37.5	37.5
		I 11		4	5	4	3	5	5	30	37.5	30	22.5	37.5	37.5
		I 13		5	4	5	2	4	3	37.5	30	37.5	15	30	22.5
		I 15		4	3	4	2	2	4	30	22.5	30	15	15	30
		I 18		4	5	5	4	5	4	30	37.5	37.5	30	37.5	30
		I 22		4	5	5	4	4	5	30	37.5	37.5	30	30	37.5
		I 24		4	5	5	3	4	5	30	37.5	37.5	22.5	30	37.5

Experience range (e)	Weighting Factor (w)	Interview (i)		Responses (r)						Responses x Weighting Factor (rw)					
				M1	M2	M3	M4	M4	M6	M1	M2	M3	M4	M5	M6
		I 26		3	5	4	3	5	5	22.5	37.5	30	22.5	37.5	37.5
		I 27		4	5	5	3	4	5	30	37.5	37.5	22.5	30	37.5
		I 29		4	5	4	3	5	5	30	37.5	30	22.5	37.5	37.5
		I 33		3	4	4	5	4	4	22.5	30	30	37.5	30	30
		I 35		5	3	4	2	3	5	37.5	22.5	30	15	22.5	37.5
		I 37		3	4	3	4	3	4	22.5	30	22.5	30	22.5	30
		I 39		3	4	4	5	4	3	22.5	30	30	37.5	30	22.5
more than 10 years	20	I 8	15	5	4	4	1	4	5	100	80	80	20	80	100
		I 12		4	4	5	3	5	5	80	80	100	60	100	100
		I 14		4	4	5	3	5	5	80	80	100	60	100	100
		I 16		5	4	3	2	3	4	100	80	60	40	60	80
		I 17		4	4	4	4	4	4	80	80	80	80	80	80
		I 21		4	5	5	3	4	5	80	100	100	60	80	100
		I 23		3	5	5	4	4	5	60	100	100	80	80	100
		I 25		4	5	5	3	4	5	80	100	100	60	80	100
		I 28		3	5	5	4	5	5	60	100	100	80	100	100
		I 30		4	5	5	4	5	5	80	100	100	80	100	100
		I 31		4	5	5	4	5	5	80	100	100	80	100	100
		I 32		4	5	5	3	5	4	80	100	100	60	100	80
		I 36		4	5	5	4	5	4	80	100	100	80	100	80
		I 38		5	5	5	3	5	5	100	100	100	60	100	100
		I 40		4	5	5	4	5	4	80	100	100	80	100	80

Then, for each challenge, we calculated the weighted sum of all responses. This sum was divided by the total weighting, i.e., the sum of the weighting factors multiplied by the number of respondents in each category $\left(\frac{\sum rw_i}{\sum w_i \times i}\right)$

6M category	**Score**
[Man]	3,96
[Methods]	4,58
[Materials]	4,66
[Machines]	3,34
[Measurement]	4,43
[Management]	4,54

Appendix 3-4. Detailed Roadmap: Challenges, Objectives, and Actions Across SBSC Perspectives

Perspective	Definition	Objectives	Challenges		Key actions	Expected impact
Learning & Growth	Aims to build the internal capacity needed for reliable Scope 3 emissions management by strengthening human skills, modernizing digital tools, and reinforcing organizational structures. It addresses foundational limitations across human, informational, and organizational capital that hinder accurate data tracking, calculation, and integration.	**Human:** Improve staff capabilities in emissions-related tasks and foster collaboration across teams	C03	Driver	- Deploy targeted training (e.g., supplier engagement, and verification practices) - Automate data entry to reduce human error	- Increased technical proficiency and reduced human error in emissions tracking - More efficient, accurate, and automated emissions reporting systems - Improved internal coordination, transparency, and accountability in Scope 3 management
			C04	Autonomous		
		Informational: Upgrade digital infrastructure for more efficient data processing	C11	Driver	- Implement real-time analytics and automated emission factor assignments - Adopt automated tools for supplier-specific data collection and curation	
			C12	Autonomous		
		Organizational: Reinforce governance, internal communication, and knowledge standardization.	C01	Peloton	- Establish standardized communication protocols - Develop shared taxonomies and harmonized templates - Create cross-functional governance teams	
			C08	Driver		
Methodological	Focuses on establishing a scientifically robust, standardized, and verifiable approach to Scope 3 emissions accounting. It ensures methodological consistency across data collection, calculation, and reporting, while aligning internal practices with international standards	Build a consistent and transparent emissions accounting methodology that ensures traceability and aligns with globally recognized frameworks.	C06	Peloton	- Tiered data strategy (prioritize primary/hybrid data) - Centralized repositories & standardized templates - Supplier disclosure mandates - Benchmark against SBTi/CSRD - Harmonized, sector-specific methodologies via secure digital platforms - Incentives structures to align with standardized reporting practices.	- More accurate, transparent, and consistent emissions inventories. - Greater credibility of Scope 3 data among stakeholders and auditors. - Improved comparability across suppliers, sectors, and reporting periods. - Enhanced alignment with regulatory and voluntary sustainability standards. - Reliable foundation for decision-making and climate performance tracking.
			C07	Peloton		
			C09	Linkage		
			C15	Linkage		

Perspective	Definition	Objectives	Challenges		Key actions	Expected impact
Internal Process	Focuses on embedding emissions tracking and governance mechanisms directly into procurement operations, audits, and decision-making processes. It ensures that Scope 3 considerations are institutionalized through policies, KPIs, and regulatory alignment, creating a structured and accountable approach to sustainable procurement.	Establish a structured framework where emissions are systematically monitored and integrated into procurement workflows, audits, and policy alignment.	C15	Linkage	- Embed carbon-related KPIs into procurement decision-making - Align internal guidelines with external regulatory frameworks (e.g., CSRD) - Integrate Scope 3 into internal audits and performance evaluations	- Scope 3 emissions become a standardized component of procurement operations - Decision-making aligns more closely with climate and compliance goals - Improved traceability and performance monitoring of emissions-related actions - Strengthened internal accountability and readiness for regulatory audits - Clear integration of sustainability within core business operations
			C16	Linkage		
Stakeholder and Supplier	Focuses on strengthening external collaboration and data exchange across the value chain to improve the accuracy, comparability, and trustworthiness of Scope 3 emissions reporting. It emphasizes active engagement with suppliers through digital platforms, formalized disclosure requirements, alignment with global frameworks, and inclusive support for SMEs.	Strengthen relationships with suppliers and stakeholders to build trust, improve data quality, and harmonize emissions practices across the value chain	C01	Peloton	- Encourage data sharing and comparability via digital platforms - Mandate emissions disclosure through procurement contracts - Align stakeholder practices with recognized frameworks - Provide technical and financial support especially for SMEs - Co-develop sector-specific methodologies to align stakeholder practices	- Enhanced trust, transparency, and collaboration across the supply chain - More consistent and comparable emissions data from diverse suppliers - Increased supplier accountability through formal reporting requirements - Empowered SMEs actively participating in sustainability reporting - Harmonized methodologies leading to credible, sector-aligned Scope 3 disclosures
			C02	Autonomous		
			C05	Autonomous		
			C09	Linkage		
			C16	Linkage		
Sustainability	Ensures that procurement strategies are proactively aligned with the organization's broader	Position procurement as a strategic tool to advance the company's	C13	Dependent	- Align procurement targets with the organization's sustainability roadmap	- Procurement becomes a key driver of the company's climate and circularity targets

Perspective	Definition	Objectives	Challenges		Key actions	Expected impact
	environmental goals, including climate action and circular economy principles. It moves beyond simple regulatory compliance to embed sustainability into sourcing decisions, specifications, and supplier relationships.	climate roadmap, support low-carbon innovation, and integrate circular economy principles	C14	Dependent	- Prioritize low-carbon and circular solutions in product and service specifications - Strengthen data verification and collection to ensure traceable emissions reporting	- Environmental performance is embedded in sourcing and supplier evaluations - Sustainable innovations are incentivized and scaled through procurement mechanisms - Long-term environmental value is created across the supply chain
			C18	Dependent		
Financial	Focuses on integrating financial tools, incentives, and planning mechanisms into procurement to support low-carbon strategies and embed sustainability into investment decisions.	Ensure emissions tracking and reduction strategies are financially viable, budgeted, and embedded into long-term investment planning	C10	Dependent	- Create an innovation fund within procurement to pilot sustainable solutions - Link carbon data to procurement costs for carbon-adjusted budgeting - Integrate emissions performance into capital expenditure (CAPEX) planning - Adopt internal carbon pricing mechanisms	-Sustainable initiatives receive appropriate funding and prioritization -Emissions are integrated into financial planning as measurable criteria -Low-carbon investments are encouraged and financially supported -Financial decisions contribute to long-term climate goals
			C12	Autonomous		
			C17	Peloton		
			C19	Dependent		

Appendix 4-1. BETie-Derived Emission Factors (kg CO_2e/m^3) Adapted by Eiffage

Emission factors adapted from the BETie tool, representing life cycle GHG emission factors for ready-mix concrete mixes. Values are provided per compressive strength and exposure class grouping, across six standardized cement types. This table reflects Eiffage's internal efforts to extract and structure the relevant environmental data from BETie into an operational reference format. "ERROR" indicates unavailable or non-applicable combinations.

Strength and exposure classes | Cement type	**CEM I**	**CEM II/A**	**CEM II/B**	**CEM III/A**	**CEM III/B**	**CEM V/A**
Sprayed concrete	347	ERROR	ERROR	ERROR	ERROR	ERROR
C16/20 X0	142	128	110	86	67	94
C20/25 X0	167	150	130	101	79	111
C20/25 XC1-XC2	213	191	165	128	99	140
C25/30 XC1-XC2	213	191	165	128	99	140
C25/30 XC3-XC4-XF1-XD1	229	205	177	137	106	150
C25/30 XF2	245	219	189	146	113	160
C30/37 XC1-XC2-XC3-XC4-XF1-XD1	229	205	177	137	106	150
C30/37 XF2-XF3	268	240	207	160	123	175
C30/37 XD2-XS1-XS2-XA1	270	242	209	162	125	177
C30/37 XF4	280	251	217	168	130	184
C35/45 XC1-XC2-XC3-XC4-XF1-XD1-XD2-XS1-XS2-XA1	270	242	209	162	125	177
C35/45 XD3-XS3-XA2	286	256	221	171	132	188
C35/45 XF2-XF3	294	263	227	176	135	193
C35/45 XF4	296	265	229	178	137	194
C40/50 XC1-XC2-XC3-XC4-XF1-XD1-XD2-XD3-XS1-XS2-XS3-XA1-XA2	310	277	239	185	142	203
C40/50 XF2-XF3-XF4	321	287	248	193	149	211
C40/50 XA3	297	266	230	179	138	196
C45/55 XC1-XC2-XC3-XC4-XF1-XD1-XD2-XD3-XS1-XS2-XS3-XA1-XA2-XA3	327	293	252	196	151	214
C45/55 XF2-XF3-XF4	337	302	260	202	156	221
C50/60 XC1-XC2-XC3-XC4-XF1-XD1-XD2-XD3-XS1-XS2-XS3-XA1-XA2-XA3	344	308	ERROR	ERROR	ERROR	ERROR
C50/60 XF2-XF3-XF4	355	318	ERROR	ERROR	ERROR	ERROR
C60/75 XC1-XC2-XC3-XC4-XF1-XD1-XD2-XD3-XS1-XS2-XS3-XA1-XA2-XA3	347	311	ERROR	ERROR	ERROR	ERROR
C60/75 XF2-XF3-XF4	ERROR	ERROR	ERROR	ERROR	ERROR	ERROR
C80/95 - All exposure classes	335	ERROR	ERROR	ERROR	ERROR	ERROR

Supporting Information (SI) – Chapter 5

Due to the size and formatting requirements of the matrices, this document is provided as an external supporting information for readability. Access the full appendix here:

https://docs.google.com/spreadsheets/d/1lq9dTcK6J5XaO3im09emJJ6zEh9Xygox/edit?usp=sharing&ouid=101764286973883338185&rtpof=true&sd=true

Appendix 5-1. Time-Driven Activity-Based Costing: Core Calculation Procedure

According to Kaplan & Anderson (2004), the calculation methodology of the TD-ABC system consists of seven main steps.

Costs assessment based on available capacity

(1) Identify various resources, resource groups, and products; a "resource group" could be an organizational unit, department, activity or section that may consist of many different resources. (Ratnatunga et al., 2012),
(2) Estimate the total assigned budget of each resource group,
(3) Estimate the practical capacity of each resource group in terms of time (e.g. available working hours, excluding vacation, meeting and training hours). Kaplan and Anderson consider that the practical capacity is equivalent to between 80% and 85% of the theoretical full capacity (Kaplan and Anderson, 2007), Theoretical capacity refers to the total possible performance of an activity if it were running at full capacity with no interruptions or inefficiencies under ideal conditions. This capacity is often calculated based on theoretical models and assumptions without considering real-world limitations.
(4) Calculate the Capacity Cost Rate (CCR) of each resource group by dividing the total cost of the resource group by the practical capacity. CCR is a concept used to allocate costs more accurately to activities or products based on the practical capacity of resources.

Assessment of time, which is needed for required variation of running activity.

(1) Determine the time estimation for each event, based upon the time equation for the activity and the characteristics of the event; time data can be collected, in some cases, automatically, from information systems,
(2) Multiply the CCR of each activity by the time estimate for the event to calculate the unit cost of each activity per product, sum these costs to find the total cost of each product,
(3) Establish the gap between total costs (used resources) and available resources (potential time), and decide to reallocate resources to new activities or reduce resources.

Appendix 5-2. ABC-LCA Foundational Terminology

Before integrating LCA into ABC, Jourdaine et al. (2021) clarified and defined a common glossary representing concepts present in both the ABC and LCA, as both use different terminology.

Intermediate flow (ABC: resource; LCA: intermediate flow): In ABC, the term resource refers to the cost of an accounting entry, whether it comes from general or cost accounting. In LCA, this concept can be referred to as an intermediate (or economic) flow, which represents a flow with economic value including an input purchased by an organization, which results in an accounting entry. Such intermediate flow generates environmental flows (i.e., exchange with the environment) within the supply chain or its use, then leading to environmental impacts. Environmental flows are either emissions of pollutants or extractions of natural resources or, for short, resources.

Activity (ABC: activity; LCA: [sub]unit process): In ABC, the term activity refers to an operation conducted in an organisation. In LCA, a subunit process is used; a unit process is an organisation-wide process that delivers one or more products.

Product (ABC: cost object; LCA: product): In ABC, the term cost object refers to the output of the organisation for which the cost calculation is made. The corresponding LCA term is the product, which is defined as a good or service having a functional unit.

Drivers (ABC: driver; LCA: partitioning coefficient): Two types of drivers are considered according to the ABC method. An activity driver allows the allocation of economic transaction costs to an activity. A cost driver assigns economic transaction costs previously stored by an activity to an object of analysis. The corresponding concept used for LCA is the partitioning coefficient, which makes it possible to assign the environmental costs of an intermediate flow directly to the object of analysis. Because the presented approach not only is limited to the costs of an intermediate flow but also extends to its environmental impacts, the term intermediate flow driver is used. It should be noted that the multiplication of the intermediate flow driver by the activity driver provides the partitioning coefficient.

Appendix 5-3

Step 1: Identification of activities and products

In this case study, the key activities involved are as follows: a1. Administration, a2. Materials use for α, a3. Materials use for β, a4. Materials use for γ, a5. Machine use for paper packaging, a6. Machine use for plastic packaging, a7. Production management.

The company's product line includes three packaging types: α a recycled paper-based packaging, β a non-recycled paper-based packaging and γ a plastic-based packaging.

Step 2a: Identification of resources and extraction of the corresponding impact factor (IF) from PSILCA

The resources used in this case study, along with their geographical location, are as follows: Cleaning service (UK), Communication (NZ), Electricity (NZ), Electricity (UK), Industrial equipments (USA), IT service (NZ), labour costs : salary & benefits, Legal service (NZ), Marketing (NZ), Paper mills (USA), Paperboard mills (USA), Plastics packaging materials (USA), Product design service (SG), R&D (AR), Recycled paper and cardboard (UK), Road freight (UK), Sea freight (USA), Softwares & systems (JP). The extraction of corresponding impact factors is detailed in Table 0-1.

Step 2b: Identification of the cost associated to each resource and calculation of the associated social impact

Table 0-2 lists the resources used in the case study, their associated costs in $, and the corresponding social impacts.

Step 3: Definition of resource drivers

Activity drivers represent the cost drivers that link resources to specific activities, as derived from the company's accounting system. These drivers allocate resource costs and impacts to activities based on measurable factors that reflect the consumption or usage of resources, detailed in Table 0-3.

Step 4: Distribution of costs and indirect social impacts of resources to activities

This step involves allocating resource costs to specific activities and calculating the indirect social impact associated with each activity. Table 0-4 outlines the annual budget of each activity and the corresponding social impacts.

Table 0-1 Social Impacts per $1 Output for Each Resource (Matrix IF)

Matrix IF	Certified environmental management system	Fair Salary	Gender wage gap	Indigenous rights	Industrial water depletion	Promoting social responsibilty	Public sector corruption	Trade unionism	Value added (total)	Violations of employment laws and regulations
1.0 USD Industrial cleaning - GB	0.64	0.87	0.46	0.09	0.19	0.61	4.05	0.66	2.07	0.41
1.0 USD Communications - NZ	0.59	3.91	2.82	2.89	0.37	0.51	3.36	3.47	1.75	0.79
1.0 USD Electricity - NZ	0.64	2.81	2.29	2.53	0.11	0.36	2.64	2.69	1.36	0.40
1.0 USD Electricity by gas - GB	0.42	0.82	0.28	0.05	0.29	0.83	1.97	0.56	1.11	0.26
1.0 USD Other industrial machinery manufacturing - US	1.91	10.54	0.09	0.50	5.53	0.85	5.14	5.37	2.72	5.29
1.0 USD Computer software and services - NZ	3.00	5.07	4.09	4.25	0.33	2.96	4.61	4.68	2.37	0.57
1.0 USD Labour costs	-	-	-	-	-	-	-	-	-	-
1.0 USD Legal services - NZ	0.33	4.28	3.83	3.94	0.15	0.31	4.07	4.10	2.01	0.29
1.0 USD Advertising and marketing - NZ	0.75	4.91	3.78	3.91	0.34	0.79	4.38	4.45	2.18	0.85
1.0 USD Paper mills - US	2.97	6.75	0.08	0.32	3.46	2.22	3.27	3.53	1.82	3.30
1.0 USD Paperboard Mills - US	3.14	7.10	0.06	0.34	3.67	2.32	3.43	3.70	1.86	3.49
1.0 USD Plastics packaging materials and unlaminated film and sheet manufacturing - US	1.72	7.54	0.08	0.35	3.89	0.90	3.66	4.02	2.07	3.75
1.0 USD Industrial design services - SG	0.54	8.53	0.24	0.08	7.47	2.41	7.09	2.38	3.76	0.91
1.0 USD Research and development - AR	12.27	1.95	1.42	0.66	0.18	25.84	6.60	6.90	28.74	7.16
1.0 USD Recycling of paper & cardboard - GB	0.59	1.49	0.49	0.09	0.54	0.83	3.41	1.04	1.84	0.55
1.0 USD Freight transport by road - GB	0.69	0.95	0.40	0.08	0.27	0.50	3.53	0.70	1.85	0.47
1.0 USD Water transport - US	4.30	9.08	0.04	0.44	4.85	0.54	4.46	4.59	2.28	4.60
1.0 USD Electronic computing equipment (except personal computers) - JP	0.41	4.51	1.07	0.12	1.34	1.26	2.47	2.66	0.60	1.95

Table 0-2 Social Impact of Each Resource (Matrix I)

	Vector C	**Matrix I**									
	Costs ($)	Certified environmental management system	Fair Salary	Gender wage gap	Indigenous rights	Industrial water depletion	Promoting social responsibilty	Public sector corruption	Trade unionism	Value added (total)	Violations of employment laws and regulations
Cleaning service (UK)	20000	17497.9	9225.7	1822.7	3746.4	12275.1	80952.0	13235.3	41460.0	8142.3	17497.9
Communication (NZ)	120000	469281.2	338597.0	347096.4	43818.3	61303.5	403536.5	416716.5	209449.3	94632.3	469281.2
Electricity (NZ)	20000	56169.7	45782.5	50653.4	2143.7	7103.3	52800.5	53719.5	27138.3	7934.0	56169.7
Electricity (UK)	57000	46840.6	15844.9	3033.7	16722.0	47426.1	112041.8	31708.9	63373.5	14926.4	46840.6
Industrial equipments (USA)	211000	2224069.9	19298.9	105846.5	1165885.8	179833.1	1083565.5	1133553.4	574062.3	1116854.3	2224069.9
IT service (NZ)	150000	759916.4	614079.6	637869.0	49012.9	444338.8	691490.3	701805.2	355472.4	85349.7	759916.4
labour costs : salary & benefits	1218000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Legal service (NZ)	50000	213911.5	191598.8	196977.4	7724.7	15355.2	203480.4	205220.0	100702.4	14712.9	213911.5
Marketing (NZ)	280000	1374712.2	1059460.4	1094843.9	95228.2	222529.0	1226690.4	1246256.6	609044.7	237076.6	1374712.2
Paper mills (USA)	90000	607529.8	7340.9	28387.6	311111.5	199549.3	293994.2	317467.7	163352.6	297254.0	607529.8
Paperboard mills (USA)	210000	1490479.0	13083.9	70377.5	770694.0	487559.1	721208.2	777057.1	391618.3	733003.8	1490479.0
Plastics packaging materials (USA)	150000	1130369.6	11470.3	52868.6	583881.5	134817.5	549645.0	603278.5	310380.2	562417.2	1130369.6
Product design service (SG)	20000	170659.2	4762.3	1632.8	149431.1	48170.5	141895.7	47643.0	75282.2	18150.0	170659.2
R&D (AR)	20000	39042.4	28314.8	13197.0	3667.6	516814.7	132073.4	137927.5	574747.6	143103.9	39042.4
Recycled paper and cardboard (UK)	335000	497669.9	165447.9	29605.6	179310.9	276596.1	1141453.8	348683.8	615443.1	184617.1	497669.9
Road freight (UK)	25000	23641.9	9946.4	2061.1	6745.6	12582.4	88134.7	17431.9	46355.9	11804.5	23641.9
Sea freight (USA)	114000	1035409.1	4121.4	50380.5	553228.5	61437.3	507909.7	523384.9	259371.3	524181.9	1035409.1
Softwares & systems (JP)	40000	180581.1	42858.8	4773.9	53430.7	50546.8	98935.2	106321.9	23978.6	78045.0	180581.1

Table 0-3 Resource Drivers from Resources to Activities (Matrix B)

	Cleaning service (UK)	Communication (NZ)	Electricity (NZ)	Electricity (UK)	Industrial equipments (USA)	IT service (NZ)	Labour costs : salary & benefits	Legal service (NZ)	Marketing (NZ)	Paper mills (USA)	Paperboard mills (USA)	Plastics packaging materials (USA)	Product design service (SG)	R&D (AR)	Recycled paper and cardboard (UK)	Road freight (UK)	Sea freight (USA)	Softwares & systems (JP)
a1. Administration	0.00	0.83	1.00	0.00	0.00	1.00	0.33	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
a2. Materials use for α	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00
a3. Materials use for β	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.53	0.00
a4. Materials use for γ	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.47	0.00
a5. Machine use for paper packaging	0.00	0.00	0.00	0.40	0.55	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
a6. Machine use for plastic packaging	0.00	0.00	0.00	0.25	0.45	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
a7. Production management	1.00	0.17	0.00	0.35	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00

Table 0-4 Total Social Impact of Each Activity (Matrix AI)

	Cost ($)	Certified env management system	Fair Salary	Gender wage gap	Indigenous rights	Industrial water depletion	Promoting social responsibilty	Public sector corruption	Trade unionism	Value added (total)	Violations of employment laws and reg
a1. Administration	1000000	748100.6	2795777.5	2193085.6	2269590.8	190624.7	740412.5	2510741.9	2554265.1	1266898.9	423933.6
a2. Materials use for α	500000	213936.5	521311.9	175394.4	31666.7	186056.6	289178.4	1229588.4	366115.7	661799.0	196421.6
a3. Materials use for β	500000	1184437.5	2642961.0	22594.0	125281.2	1372978.4	719443.8	1282523.3	1369990.6	691482.1	1306143.0
a4. Materials use for γ	300000	490279.9	1620826.5	13422.5	76733.1	845937.2	163919.4	790233.8	851197.6	433240.3	810713.9
a5. Machine use for paper packaging	230000	229917.2	1231071.4	16911.9	58913.0	642182.9	117150.1	635778.7	630608.3	338449.3	614735.0
a6. Machine use for plastic packaging	200000	189723.5	1023403.8	12672.3	48902.8	534557.6	93468.3	520515.7	523528.1	276750.2	511808.4
a7. Production management	400000	305546.8	502429.4	147154.0	80340.2	223446.2	654665.0	560425.3	385706.4	772613.0	268450.6

Step 5a / 5b: Determination of the practical capacity and calculation of the Capacity Cost Rate CCR

All employees work under a standard 40-hour workweek contract. Additionally, the company allows for each employee 4 weeks (20 days) of holidays per year, so each employee is available for 48 weeks per year. Kaplan and Anderson consider that the practical capacity is equivalent to between 80% and 85% of the theoretical full capacity (Kaplan and Anderson, 2007). The practical capacity stands at 80% for the administration and the production management, and 85% for the other collaborators. Time is expressed in terms of minutes, as we believe they are more easily understood than fractional amounts of an hour Table 0-5 outlines the annual practical capacity (S) and the Capacity Cost Rate (CCR). $(\text{Annual practical capacity} = \text{n° of employees} \times 40 \times 48 \times (80\ldots85\%) \times 60)$

Table 0-5 Annual Practical Capacity and the Capacity Cost Rate

Activities	n° of employees	(%) of the practical capacity	Annual Practical capacity (min)	Capacity cost rate ($/min)
a1. Administration	12	80%	1105920	0,904
a2. Materials use for α	5	85%	489600	1,021
a3. Materials use for β	5	85%	489600	1,021
a4. Materials use for γ	4	85%	391680	0,766
a5. Machine use for paper packaging	5	85%	489600	0,470
a6. Machine use for plastic packaging	4	85%	391680	0,511
a7. Production management	15	80%	1382400	0,289
Total	50	-	4740480	-

Step 5c: Time estimation for each activity

The time needed to complete each activity (Table 0-6), referred to as "unit time" in TD-ABC terminology, is determined using the activity's time equation.

a1. Administration = 1 + 0.3 {if non-recycled paper} + 0.7 {if recycled paper}, **a2. Materials use for α** = 1.55, **a3. Materials use for β** = 2.15, **a4. Materials use for γ** = 1.75,

a5. Machine use for paper packaging = 1 - 0,2 {if recycled paper}, **a6. Machine use for plastic packaging** = 1,7 **a7. Production management** = 1,5 + 0,3 {if non-recycled paper} + 0,5 {if recycled paper}

Table 0-6 Time Estimation Matrix

	Matrix T : Unit time (min)		
	α	**β**	**γ**
a1. Administration	1,7	1,3	1
a2. Materials use for α	1,55	0	0
a3. Materials use for β	0	2,15	0
a4. Materials use for γ	0	0	1,75
a5. Machine use for paper packaging	0,8	1	0
a6. Machine use for plastic packaging	0	0	1,7
a7. Production management	2	1,8	1,5
Total	6,05	6,25	5,95

Step 6: Calculation of activity drivers

This step entails creating the product driver matrix, where activities are fully allocated to their respective products based on the time required for production. The activity driver table (Γ) is provided in Table 0-7. It outlines the product drivers to distribute activity costs and their social impacts to the product.

Table 0-7 Activity Drivers' Matrix

	Matrix Γ: activity drivers		
	α	**β**	**γ**
a1. Administration	1.54E-06	1.18E-06	9.04E-07
a2. Materials use for α	3.17E-06	0	0
a3. Materials use for β	0	4.39E-06	0
a4. Materials use for γ	0	0	4.47E-06
a5. Machine use for paper packaging	1.63E-06	2.04E-06	0
a6. Machine use for plastic packaging	0	0	4.34E-06
a7. Production management	1.45E-06	1.30E-06	1.09E-06

Total	1.54E-06	1.18E-06	9.04E-07

Step 7: Distribution of costs and indirect social impacts of activities to products

Table 0-8 outlines the activity costs per product, and the corresponding indirect social impacts.

Table 0-8 Activity Unit Costs and Product Unit Costs, Along with Corresponding Indirect Social Impacts

	Activity unit cost ($)		
	α	**β**	**γ**
a1. Administration	1,537	1,175	0,904
a2. Materials use for α	1,583	0	0
a3. Materials use for β	0	2,196	0
a4. Materials use for γ	0	0	1,340
a5. Machine use for paper packaging	0,376	0,470	0
a6. Machine use for plastic packaging	0	0	0,868
a7. Production management	0,579	0,521	0,434
Product unit cost (PC)	4,075	4,362	3,547
	Indirect social impacts		
Certified environmental management system	2.64	6.95	4.02
Fair Salary	8.69	18.06	14.76
Gender wage gap	4.17	2.90	2.26
Indigenous rights	3.80	3.44	2.69
Industrial water depletion	2.25	7.86	6.51
Promoting social responsibilty	3.19	5.12	2.52
Public sector corruption	9.60	10.61	8.67
Trade unionism	6.67	10.81	8.80
Value added (total)	5.71	6.22	5.12
Violations of employment laws and regulations	2.67	7.84	6.52

Step 8a: Calculation of direct social impacts per unit product

The assessment requires the researcher to assign a risk level to each impact category, ranging from very low to very high. This classification should be grounded in rigorous surveys and field studies (Chabrawi et al., 2024) to acquire precise, company-specific data. Where such data is unavailable, sector-specific generic data from the PSILCA database, for example, may serve as a viable alternative. In this case, sector-specific data were used. The calculations of direct social impact per unit of product are presented in Table 0-9.

Table 0-9 Direct Impacts per Unit Product

P_dir : direct social impacts	Certified environmental management system	Fair Salary	Gender wage gap	Indigenous rights	Industrial water depletion	Promoting social responsibilty	Public sector corruption	Trade unionism	Value added (total)	Violations of employment laws and regulations
Flow	high risk	high risk	high risk	medium risk	low risk	no data	very high risk	high risk	low risk	medium risk
Risk factor	10	10	10	1	0.1	0.1	100	10	0.1	1
α	1.0083	1.0083	1.0083	0.1008	0.0101	0.0101	10.0833	1.0083	0.0101	0.1008
β	1.0417	1.0417	1.0417	0.1042	0.0104	0.0104	10.4167	1.0417	0.0104	0.1042
γ	0.9917	0.9917	0.9917	0.0992	0.0099	0.0099	9.9167	0.9917	0.0099	0.0992

Step 8b: Calculation of total social impacts per unit product

The calculation of total social impacts per unit of product is obtained by summing the indirect and direct impacts (Table 0-10).

Table 0-10 Total Social Impacts per Unit Product

PI	Certified environmental management system	Fair Salary	Gender wage gap	Indigenous rights	Industrial water depletion	Promoting social responsibilty	Public sector corruption	Trade unionism	Value added (total)	Violations of employment laws and regulations
α	3.65	9.69	5.18	3.90	2.26	3.20	19.69	7.68	5.72	2.77
β	7.99	19.10	3.94	3.55	7.87	5.13	21.03	11.85	6.23	7.94
γ	5.01	15.75	3.25	2.79	6.52	2.53	18.58	9.80	5.13	6.62

Step 9 : Handling unused capacity and impact allocation (See SI p. 5)

References

© Carbon+Alt+Delete, 2025. The spend-based method as a low-effort and appropriate starting point. URL https://support.carbonaltdelete.eu/article/81-spend-based-emission-factors (accessed 7.27.25).

AAA, 1966. A Statement of Basic Accounting Theory, American Accounting Association.

Abou Taleb, M., Al Farooque, O., 2021. Towards a circular economy for sustainable development: An application of full cost accounting to municipal waste recyclables. J. Clean. Prod. 280, 124047. https://doi.org/10.1016/j.jclepro.2020.124047

Abubakr, A.A.M., Sahal, M.S.G., Mohammed, A.A.A., Yousif, N.A.I., Mohammed, F.M.A., Roustom, Z.M., 2024. Challenges of Disclosing Environmental Accounting Performance and Its Impact on Quality Supply Chains to Promote Sustainable Development in Companies—Experiences of Some Companies in the GCC—2024. Sustainability 16, 11243. https://doi.org/10.3390/su162411243

Acquaye, A.A., Wiedmann, T., Feng, K., Crawford, R.H., Barrett, J., Kuylenstierna, J., Duffy, A.P., Koh, S.C.L., McQueen-Mason, S., 2011. Identification of 'Carbon Hot-Spots' and Quantification of GHG Intensities in the Biodiesel Supply Chain Using Hybrid LCA and Structural Path Analysis. Environ. Sci. Technol. 45, 2471–2478. https://doi.org/10.1021/es103410q

ADEME, 2023a. Base carbone® [WWW Document]. URL https://data.ademe.fr/datasets/undefined (accessed 7.22.25).

ADEME, 2023b. Base Empreinte : vers un outil unique au service de la comptabilité environnementale. ADEME Infos. URL https://infos.ademe.fr/magazine-avril-2023/dossier/base-empreinte-vers-un-outil-unique-au-service-de-la-comptabilite-environnementale/ (accessed 7.22.25).

Afnor, 2021. NF EN 206+A2.

Afnor, 2019. EN 15804+A2.

Afonso, P., Paisana, A., 2009. An Algorithm for Activity Based Costing based on Matrix Multiplication. IEEM 2009 - IEEE Int. Conf. Ind. Eng. Eng. Manag. https://doi.org/10.1109/IEEM.2009.5372875

Agez, M., Majeau-Bettez, G., Margni, M., Strømman, A.H., Samson, R., 2020a. Lifting the veil on the correction of double counting incidents in hybrid life cycle assessment. J. Ind. Ecol. 24, 517–533. https://doi.org/10.1111/jiec.12945

Agez, M., Muller, E., Bulle, C., Debarre, L., Seitfudem, G., Viveros Santos, I., Duval, L., 2024. IMPACT World+ / a globally regionalized method for life cycle impact assessment. https://doi.org/10.5281/zenodo.14041258

Agez, M., Wood, R., Margni, M., Strømman, A.H., Samson, R., Majeau-Bettez, G., 2020b. Hybridization of complete PLCA and MRIO databases for a comprehensive product system coverage. J. Ind. Ecol. 24, 774–790. https://doi.org/10.1111/jiec.12979

Agrawal, R., Islam, N., Samadhiya, A., Shukla, V., Kumar, A., Upadhyay, A., 2025. Paving the way to environmental sustainability: A systematic review to integrate big data analytics into high-stake decision forecasting. Technol. Forecast. Soc. Change 214, 124060. https://doi.org/10.1016/j.techfore.2025.124060

Aguiar, A., Chepeliev, M., Corong, E., Mensbrugghe, D. van der, 2022. The Global Trade Analysis Project (GTAP) Data Base: Version 11. J. Glob. Econ. Anal. 7. https://doi.org/10.21642/JGEA.070201AF

AICPA, 1970. APB accounting principles, Accounting Principles Board.

AICPA, 1941. Accounting terminology: Preliminary report of a Special Committee on Terminology. AICPA Comm.

Aigner, J., 2024. Workshop 03: Navigating methodological inconsistencies in Scope 3 accounting & LCA | FSLCI e.V. URL https://fslci.org/lcic/lcic2024/lcic2024-workshops/workshop-03-navigating-methodological-inconsistencies-in-scope-3-accounting-lca/ (accessed 11.8.24).

Akella, S., Sen, R., Gokarn, K., Mahasuwan, P., 2024. CAPACITY BUILDING MODULE SUSTAINABLE PUBLIC PROCUREMENT.

Alejandrino, C., Mercante, I.T., Bovea, M.D., 2022. Combining O-LCA and O-LCC to support circular economy strategies in organizations: Methodology and case study. J. Clean. Prod. 336, 130365. https://doi.org/10.1016/j.jclepro.2022.130365

Allen, S.D., Zhu, Q., Sarkis, J., 2021. Expanding conceptual boundaries of the sustainable supply chain management and circular economy nexus. Clean. Logist. Supply Chain 2, 100011. https://doi.org/10.1016/j.clscn.2021.100011

Alvarez, S., Blanquer, M., Rubio, A., 2014. Carbon footprint using the Compound Method based on Financial Accounts. The case of the School of Forestry Engineering, Technical University of Madrid. J. Clean. Prod. 66, 224–232. https://doi.org/10.1016/j.jclepro.2013.11.050

Alzahmi, W., Al-Assaf, K., Alshaikh, R., Bahroun, Z., 2025. Towards Sustainable ERP Systems: Emerging Trends, Challenges, and Future Pathways. Manag. Syst. Prod. Eng. 33, 24–38. https://doi.org/10.2478/mspe-2025-0003

Anastasiou, D., Ballis, A., Guizani, A., Kallandranis, C., Lakhal, F., 2024. Monetary policy impact on sustainability: Analyzing interest rates and corporate carbon emissions. J. Environ. Manage. 368, 122119. https://doi.org/10.1016/j.jenvman.2024.122119

Anaya, L., Hustad, E., Olsen, D.H., 2025. How do ERP systems contribute to sustainable development? a case study of two Middle Eastern enterprises. Procedia Comput. Sci., CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies 256, 407–414. https://doi.org/10.1016/j.procs.2025.02.136

Anaya, L., Qutaishat, F., 2022. ERP systems drive businesses towards growth and sustainability. Procedia Comput. Sci., International Conference on Industry Sciences and Computer Science Innovation 204, 854–861. https://doi.org/10.1016/j.procs.2022.08.103

Anilkumar E.N., Sridharan R., 2019. Sustainable Supply Chain Management: A Literature Review and Implications for Future Research. Int. J. Syst. Dyn. Appl. 8, 15–52. https://doi.org/10.4018/IJSDA.2019070102

Anthonissen, J., Van Troyen, D., Braet, J., Van den bergh, W., 2015. Using carbon dioxide emissions as a criterion to award road construction projects: a pilot case in Flanders. J. Clean. Prod. 102, 96–102. https://doi.org/10.1016/j.jclepro.2015.04.020

Antić, L., Stevanović, T., Milenović, J., 2021. Environmental activity-based costing as an instrument of environmental management accounting. Ekon. Pogl. 23, 53–68. https://doi.org/10.5937/ekopogl2101053a

Apple, 2022. Apple calls on global supply chain to decarbonize by 2030. Apple Newsroom.

Arcese, G., Lucchetti, M.C., Massa, I., Valente, C., 2018. State of the art in S-LCA: integrating literature review and automatic text analysis. Int. J. Life Cycle Assess. 23, 394–405. https://doi.org/10.1007/s11367-016-1082-0

Asdrubali, F., Grazieschi, G., Gandola, D.M., 2025. The Role of Environmental Product Declarations in the Decarbonization of Building Materials and Components. Energies 18, 1308. https://doi.org/10.3390/en18051308

ASIC, 2024. 24-205 MR ASIC urges businesses to prepare for mandatory climate reporting.

Assuncao, M., 2023. A practical guide to calculating a product's carbon footprint using LCA. Glob. Clim. Initiat. URL https://globalclimateinitiatives.com/en/guide-pratique-pour-calculer-lempreinte-carbone-dun-produit-par-lacv/ (accessed 11.14.24).

Audencia, 2022. LIFTS accounting model © [WWW Document]. URL https://multi-capital-performance.audencia.com/en/research-and-studies/lifts-accounting-modelc/

Ayadi, A., Auffan, M., Rose, J., 2020. Ontology-based NLP information extraction to enrich nanomaterial environmental exposure database. Procedia Comput. Sci., Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 24th International Conference KES2020 176, 360–369. https://doi.org/10.1016/j.procs.2020.08.037

Ayassamy, P., Pellerin, R., 2023. Social Life-Cycle Assessment in the Construction Industry: A Review of Characteristics, Limitations, and Challenges of S-LCA through Case Studies. Sustainability 15, 14569. https://doi.org/10.3390/su151914569

Ayinla, B.S., Ike, C.U., Asuzu, O.F., Atadoga, A., Ndubuisi, N.L., Adeleye, R.A., Ayinla, B.S., Ike, C.U., Asuzu, O.F., Atadoga, A., Ndubuisi, N.L., Adeleye, R.A., 2024. Environmental costing and sustainable accounting: A comprehensive review: Delving into methods of accounting for environmental impacts in financial statements. World J. Adv. Res. Rev. 21, 235–251. https://doi.org/10.30574/wjarr.2024.21.2.0439

Baboulet, O., Lenzen, M., 2010. Evaluating the environmental performance of a university. J. Clean. Prod. 18, 1134–1141. https://doi.org/10.1016/j.jclepro.2010.04.006

Backes, J.G., Hinkle-Johnson, R., Traverso, M., 2023. The influence of the Functional Unit on the comparability of life cycle assessments in the construction sector: A Systematic Literature Review and attempt at unification for Reinforced Concrete. Case Stud. Constr. Mater. 18, e01966. https://doi.org/10.1016/j.cscm.2023.e01966

Backes, J.G., Traverso, M., 2021. Application of Life Cycle Sustainability Assessment in the Construction Sector: A Systematic Literature Review. Processes 9, 1248. https://doi.org/10.3390/pr9071248

Baddley, J., Rasheed, F.N., 2023. The Aga Khan Development Network's (AKDN) approach to supply chain carbon foot printing for healthcare providers. Clean. Logist. Supply Chain 7, 100109. https://doi.org/10.1016/j.clscn.2023.100109

Baehr, J., Zenglein, F., Sonnemann, G., Lederer, M., Schebek, L., 2024. Back in the Driver's Seat: How New EU Greenhouse-Gas Reporting Schemes Challenge Corporate Accounting. Sustainability 16, 3693. https://doi.org/10.3390/su16093693

Balcioglu, G., Fitzgerald, A.M., Rodes, F.A.M., Allen, S.R., 2025. Data quality and uncertainty assessment of life cycle inventory data for composites. Compos. Part B Eng. 292, 112021. https://doi.org/10.1016/j.compositesb.2024.112021

Bamana, G., Miller, J.D., Young, S.L., Dunn, J.B., 2021. Addressing the social life cycle inventory analysis data gap: Insights from a case study of cobalt mining in the Democratic Republic of the Congo. One Earth 4, 1704–1714. https://doi.org/10.1016/j.oneear.2021.11.007

Bartoli, A., Hamelin, L., Rozakis, S., Borzęcka, M., Brandão, M., 2019. Coupling economic and GHG emission accounting models to evaluate the sustainability of biogas policies. Renew. Sustain. Energy Rev. 106, 133–148. https://doi.org/10.1016/j.rser.2019.02.031

Bauld, S., 2022. Procurement Perspectives: Poor specifications may force bidders to guess. Dly. Commer. News. URL https://canada.constructconnect.com/dcn/news/government/2022/04/procurement-perspectives-poor-specifications-may-force-bidders-to-guess (accessed 7.23.25).

Bebbington, J., Unerman, J., 2018. Achieving the United Nations Sustainable Development Goals: An enabling role for accounting research. Account. Audit. Amp Account. J. 31, 2–24. https://doi.org/10.1108/AAAJ-05-2017-2929

Bellini, B., Mathieu, M., 2017. Projet SeMA : Sense-Making Accounting Pour une Comptabilité de Sens.

Benoît, C., Norris, G.A., Valdivia, S., Ciroth, A., Moberg, A., Bos, U., Prakash, S., Ugaya, C., Beck, T., 2010. The guidelines for social life cycle assessment of products: just in time! Int. J. Life Cycle Assess. 15, 156–163. https://doi.org/10.1007/s11367-009-0147-8

Benoit-Norris, C., Bennema, M., Norris, G., 2018. THE SOCIAL HOTSPOTS DATABASE Supporting documentation Update 2019.

Bergeron, H., 2010. Chapitre 15. Développement durable : les apports et les limites de la comptabilité, in: Le développement durable. Dunod, pp. 227–242. https://doi.org/10.3917/dunod.wolff.2010.01.0227

Bergerson, J.A., Brandt, A., Cresko, J., Carbajales-Dale, M., MacLean, H.L., Matthews, H.S., McCoy, S., McManus, M., Miller, S.A., Morrow, W.R., Posen, I.D., Seager, T., Skone, T., Sleep, S., 2020. Life cycle assessment of emerging technologies: Evaluation techniques at different stages of market and technical maturity. J. Ind. Ecol. 24, 11–25. https://doi.org/10.1111/jiec.12954

Bernardini, C., Máñez Costa, M., Molinari, F., 2025. Climate proofing of public procurement: a gap to be filled. Npj Clim. Action 4, 2. https://doi.org/10.1038/s44168-024-00207-0

Berry, M.A., Rondinelli, D.A., 1998. Proactive corporate environmental management: A new industrial revolution. Acad. Manag. Perspect. 12, 38–50. https://doi.org/10.5465/ame.1998.650515

Bertalanffy, L. von, 1968. General System Theory: Foundations, Development, Applications.

Biswas, D., Jahan, S., Saha, S., Samsuddoha, Md., 2024. A succinct state-of-the-art survey on green cloud computing: Challenges, strategies, and future directions. Sustain. Comput. Inform. Syst. 44, 101036. https://doi.org/10.1016/j.suscom.2024.101036

Bjørn, A., Owsianiak, M., Molin, C., Hauschild, M.Z., 2018. LCA History, in: Hauschild, M.Z., Rosenbaum, R.K., Olsen, S.I. (Eds.), Life Cycle Assessment: Theory and Practice. Springer International Publishing, Cham, pp. 17–30. https://doi.org/10.1007/978-3-319-56475-3_3

Blanchy, G., Albrecht, L., Koestel, J., Garré, S., 2023. Potential of natural language processing for metadata extraction from environmental scientific publications. SOIL 9, 155–168. https://doi.org/10.5194/soil-9-155-2023

Blanco, C., Caro, F., Corbett, C.J., 2016. The state of supply chain carbon footprinting: analysis of CDP disclosures by US firms. J. Clean. Prod. 135, 1189–1197. https://doi.org/10.1016/j.jclepro.2016.06.132

BlueOn [WWW Document], n.d. URL https://blueon.io/ (accessed 7.27.25).

Bonilla-Alicea, R.J., Fu, K., 2021. Evaluation of a challenge-derived social life cycle assessment (S-LCA) framework. Int. J. Sustain. Eng. 14, 1680–1697. https://doi.org/10.1080/19397038.2021.2004258

Borschewski, D., Weber, S., Albrecht, S., Leistner, P., 2024. Mastering complexity in Life Cycle Assessment for product development: Evaluating the impacts of adaptive façades. Sustain. Prod. Consum. 49, 341–353. https://doi.org/10.1016/j.spc.2024.07.004

Bouillass, G., Blanc, I., Perez-Lopez, P., 2021. Step-by-step social life cycle assessment framework: a participatory approach for the identification and prioritization of impact subcategories applied to mobility scenarios. Int. J. Life Cycle Assess. 26, 2408–2435. https://doi.org/10.1007/s11367-021-01988-w

Bové, A.-T., Swartz, S., 2016. Starting at the source: Sustainability in supply chains | McKinsey&Company.

Brunner, P.H., Rechberger, H., 2016. Handbook of Material Flow Analysis, 0 ed. CRC Press. https://doi.org/10.1201/9781315313450

Bueno, G., de Blas, M., Pérez-Iribarren, E., Zuazo, I., Torre-Pascual, E., Erauskin, A., Etxano, I., Tamayo, U., García, M., Akizu-Gardoki, O., León, I., Marieta, C., Saez de Cámara, E., Zulueta, G., Barrio, I., 2022. Dataset on the environmental and social footprint of the University of the Basque Country UPV/EHU. Data Brief 41, 107847. https://doi.org/10.1016/j.dib.2022.107847

Bueno, G., De Blas, M., Pérez-Iribarren, E., Zuazo, I., Torre-Pascual, E., Erauskin, A., Etxano, I., Tamayo, U., García, M., Akizu-Gardoki, O., León, I., Marieta, C., Zulueta, G., Barrio, I., 2021. The environmental and social footprint of the university of the Basque Country UPV/EHU. J. Clean. Prod. 315, 128019. https://doi.org/10.1016/j.jclepro.2021.128019

Bullard, C.W., Penner, P.S., Pilati, D.A., 1978. Net energy analysis: Handbook for combining process and input-output analysis. Resour. Energy 1, 267–313. https://doi.org/10.1016/0165-0572(78)90008-7

Bulle, C., Margni, M., Patouillard, L., Boulay, A.-M., Bourgault, G., De Bruille, V., Cao, V., Hauschild, M., Henderson, A., Humbert, S., Kashef-Haghighi, S., Kounina, A., Laurent, A., Levasseur, A., Liard, G., Rosenbaum, R.K., Roy, P.-O., Shaked, S., Fantke, P., Jolliet, O., 2019. IMPACT World+: a globally regionalized life cycle impact assessment method. Int. J. Life Cycle Assess. 24, 1653–1674. https://doi.org/10.1007/s11367-019-01583-0

Bush, R., Jacques, D.A., Scott, K., Barrett, J., 2014. The carbon payback of micro-generation: An integrated hybrid input–output approach. Appl. Energy 119, 85–98. https://doi.org/10.1016/j.apenergy.2013.12.063

Busse, C., Schleper, M.C., Niu, M., Wagner, S.M., 2016. Supplier development for sustainability: contextual barriers in global supply chains. Int. J. Phys. Distrib. Logist. Manag. 46, 442–468. https://doi.org/10.1108/IJPDLM-12-2015-0300

Byrne, D., 2024. ESG: A comprehensive guide. Corp. Gov. Inst. URL https://www.thecorporategovernanceinstitute.com/insights/guides/esg-a-comprehensive-guide-to-environmental-social-and-governance-principles/ (accessed 7.25.25).

Caby, J., Hirigoyen, G., Prat dit Hauret, C., 2013. Création de valeur et gouvernance de l'entreprise -.

California Legislature, 2023. SB 253- Climate Corporate Data Accountability Act.

Catena-X, 2024. Catena-X - An Overview.

CDP, 2023. CDP Climate Change 2023 Reporting Guidance, Carbon Disclosure Project.

CDP Supply Chain, n.d. CDP Supply Chain Membership [WWW Document]. URL https://www.cdp.net (accessed 7.27.25).

CEA, BRGM, 2023. Analysis of the JRC Harmonized rules for the calculation of Carbon Footprint of Electric Vehicle Batteries.

Cerutti, A.K., Ardente, F., Contu, S., Donno, D., Beccaro, G.L., 2018. Modelling, assessing, and ranking public procurement options for a climate-friendly catering service. Int. J. Life Cycle Assess. 23, 95–115. https://doi.org/10.1007/s11367-017-1306-y

Cerutti, A.K., Contu, S., Ardente, F., Donno, D., Beccaro, G.L., 2016. Carbon footprint in green public procurement: Policy evaluation from a case study in the food sector. Food Policy 58, 82–93. https://doi.org/10.1016/j.foodpol.2015.12.001

Chabrawi, A., Andrade, J., Ugaya, C., Traverso, M., 2024. Towards reliable primary data collection and harmonized set of indicators in S-LCA on the stakeholder worker. Int. J. Life Cycle Assess. 1–19. https://doi.org/10.1007/s11367-024-02400-z

Chen, G., Shan, Y., Hu, Y., Tong, K., Wiedmann, T., Ramaswami, A., Guan, D., Shi, L., Wang, Y., 2019. Review on City-Level Carbon Accounting. Environ. Sci. Technol. 53, 5545–5558. https://doi.org/10.1021/acs.est.8b07071

Chen, J., Bao, H., Pei, L.-K., 2023. Research on carbon footprint measurement and emissions reduction optimization of the beer supply chain in China. Environ. Sci. Pollut. Res. 30, 100701–100716. https://doi.org/10.1007/s11356-023-29110-7

Chen, X., Matthews, H.S., Griffin, W.M., 2021. Uncertainty caused by life cycle impact assessment methods: Case studies in process-based LCI databases. Resour. Conserv. Recycl. 172, 105678. https://doi.org/10.1016/j.resconrec.2021.105678

Cho, H., Ackom, E., 2025. Artificial Intelligence (AI)-driven approach to climate action and sustainable development. Nat. Commun. 16, 1228. https://doi.org/10.1038/s41467-024-53956-1

Cimprich, A., Santillán-Saldivar, J., Thiel, C.L., Sonnemann, G., Young, S.B., 2019. Potential for industrial ecology to support healthcare sustainability: Scoping review of a fragmented literature and conceptual framework for future research. J. Ind. Ecol. 23, 1344–1352. https://doi.org/10.1111/jiec.12921

Cimprich, A., Young, S.B., 2023. Environmental footprinting of hospitals: Organizational life cycle assessment of a Canadian hospital. J. Ind. Ecol. 27, 1335–1353. https://doi.org/10.1111/jiec.13425

Ciroth, A., 2021. Data Quality in Life Cycle Inventories, in: LCA Compendium – The Complete World of Life Cycle Assessment. Springer International Publishing, Cham, pp. 97–122. https://doi.org/10.1007/978-3-030-62270-1_5

Ciroth, A., Theret, J.-P., Fliegner, M., Srocka, M., Bläsig, V., Duyan, Ö., 2013. Integrating life cycle assessment tools and information with product life cycle management.

Clift, R., Druckman, A. (Eds.), 2016. Taking Stock of Industrial Ecology. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-319-20571-7

Climatiq, n.d. Climatiq - API for Carbon Footprint Calculations [WWW Document]. URL https://www.climatiq.io (accessed 7.27.25).

CNA, 2024. Décarboner nos Achats. Conseil National des Achats.

Comoli, M., Tettamanzi, P., Murgolo, M., 2023. Accounting for 'ESG' under Disruptions: A Systematic Literature Network Analysis. Sustain. Switz. 15. https://doi.org/10.3390/su15086633

Cooper, R., Kaplan, R.S., 1988. Measure Costs Right: Make the Right Decisions. Harv. Bus. Rev.

Costa, D., Quinteiro, P., Dias, A.C., 2019. A systematic review of life cycle sustainability assessment: Current state, methodological challenges, and implementation issues. Sci. Total Environ. 686, 774–787. https://doi.org/10.1016/j.scitotenv.2019.05.435

Costa, D., Quinteiro, P., Pereira, V., Dias, A.C., 2022. Social life cycle assessment based on input-output analysis of the Portuguese pulp and paper sector. J. Clean. Prod. 330, 129851. https://doi.org/10.1016/j.jclepro.2021.129851

Crawford, R.H., Bontinck, P.-A., Stephan, A., Wiedmann, T., Yu, M., 2018. Hybrid life cycle inventory methods – A review. J. Clean. Prod. 172, 1273–1288. https://doi.org/10.1016/j.jclepro.2017.10.176

Cucchi, M., Volpi, L., Ferrari, A.M., García-Muiña, F.E., Settembre-Blundo, D., 2023. Industry 4.0 real-world testing of dynamic organizational life cycle assessment (O-LCA) of a ceramic tile manufacturer. Environ. Sci. Pollut. Res. 30, 124546–124565. https://doi.org/10.1007/s11356-022-20601-7

Curran, M.A., 2016. Goal and Scope Definition in Life Cycle Assessment -, Springer.

Dadhich, P., Genovese, A., Kumar, N., Acquaye, A., 2015. Developing sustainable supply chains in the UK construction industry: A case study. Int. J. Prod. Econ. 164, 271–284. https://doi.org/10.1016/j.ijpe.2014.12.012

Damiani, M., Ferrara, N., Ardente, F., 2022. Understanding Product Environmental Footprint and Organisation Environmental Footprint methods. https://doi.org/10.2760/11564

de Camargo, A.M., Forin, S., Macedo, K., Finkbeiner, M., Martínez-Blanco, J., 2019. The implementation of organizational LCA to internally manage the environmental impacts of a broad product portfolio: an example for a cosmetics, fragrances, and toiletry provider. Int. J. Life Cycle Assess. 24, 104–116. https://doi.org/10.1007/s11367-018-1502-4

de Salles, A.C.N., Brantsch, P., 2025. How Life Cycle Assessment Supports Sustainability Reporting: Example from Clean Aviation. Eng. Proc. 90, 56. https://doi.org/10.3390/engproc2025090056

de Souza Barbosa, A., da Silva, M.C.B.C., da Silva, L.B., Morioka, S.N., de Souza, V.F., 2023. Integration of Environmental, Social, and Governance (ESG) criteria: their impacts on corporate sustainability performance. Humanit. Soc. Sci. Commun. 10, 1–18. https://doi.org/10.1057/s41599-023-01919-0

Demeere, N., Stouthuysen, K., Roodhooft, F., 2009. Time-driven activity-based costing in an outpatient clinic environment: development, relevance and managerial impact. Health Policy Amst. Neth. 92, 296–304. https://doi.org/10.1016/j.healthpol.2009.05.003

Demeter, C., Lin, P.-C., Sun, Y.-Y., Dolnicar, S., 2021. Assessing the carbon footprint of tourism businesses using environmentally extended input-output analysis. J. Sustain. Tour. 30, 128–144. https://doi.org/10.1080/09669582.2021.1924181

Denise, 2024. SECR Intensity Ratios, Explained. ClearVUE.Business. URL https://clearvue.business/secr-intensity-ratios-explained/ (accessed 7.5.25).

Devlin, J., Chang, M.-W., Lee, K., Toutanova, K., 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. https://doi.org/10.48550/arXiv.1810.04805

Dhirasasna, N., Sahin, O., 2019. A Multi-Methodology Approach to Creating a Causal Loop Diagram. Systems 7, 42. https://doi.org/10.3390/systems7030042

Diebel, W., Gualandris, J., Klassen, R.D., 2024. How do suppliers respond to institutional complexity? Examining voluntary public environmental disclosure in a global manufacturing supply network. J. Oper. Manag. 70, 285–315. https://doi.org/10.1002/joom.1293

Ding, H., Zhao, Q., An, Z., Xu, J., Liu, Q., 2015. Pricing strategy of environmental sustainable supply chain with internalizing externalities. Int. J. Prod. Econ., Current Research Issues in Production Economics 170, 563–575. https://doi.org/10.1016/j.ijpe.2015.05.016

Donati, F., Aguilar-Hernandez, G.A., Sigüenza-Sánchez, C.P., De Koning, A., Rodrigues, J.F.D., Tukker, A., 2020. Modeling the circular economy in environmentally extended input-output tables: Methods, software and case study. Resour. Conserv. Recycl. 152, 104508. https://doi.org/10.1016/j.resconrec.2019.104508

Dong, Y.H., Ng, S.T., 2015. A social life cycle assessment model for building construction in Hong Kong. Int. J. Life Cycle Assess. 20, 1166–1180. https://doi.org/10.1007/s11367-015-0908-5

Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., Zaklan, A., 2021. The impact of carbon disclosure mandates on emissions and financial operating performance. Rev. Account. Stud. 26, 1137–1175. https://doi.org/10.1007/s11142-021-09611-x

Dragomir, V.D., Dumitru, M., Perevoznic, F.M., 2023. Carbon reduction and energy transition targets of the largest European companies: An empirical study based on institutional theory. Clean. Prod. Lett. 4, 100039. https://doi.org/10.1016/j.clpl.2023.100039

Dunfjäll, M., 2025. Materiality in Transition: Challenges and Opportunities in Corporate Sustainability Reporting under the CSRD. Eur. J. Risk Regul. 1–15. https://doi.org/10.1017/err.2025.10016

Dunuwila, P., Daigo, I., Rodrigo, V.H.L., Liyanage, D.J.T.S., Gong, W.T., Hatayama, H., Shobatake, K., Tahara, K., Hoshino, T., 2025. Social Life Cycle Assessment Methodology to Capture "More-Good" and "Less-Bad" Social Impacts—Part 1: A Methodological Framework. Sustainability 17, 4830. https://doi.org/10.3390/su17114830

Eccles, R.G., Ioannou, I., Serafeim, G., 2014. The Impact of Corporate Sustainability on Organizational Processes and Performance. Manag. Sci. 60, 2835–2857. https://doi.org/10.1287/mnsc.2014.1984

Eco Platform, n.d. About EPD - Eco Platform en [WWW Document]. URL https://www.eco-platform.org/eco-epd-40.html (accessed 7.22.25).

EcoVadis, n.d. 2025-02 FR SEM Enterprise. EcoVadis. URL https://ecovadis.com/lp/2025-02-fr-sem-enterprise/ (accessed 7.27.25).

EEA, 2021. Improving the climate impact of raw material sourcing. European Environmental Agency.

Eiffage, 2024. Eiffage Acteur de référence d'une Europe bas carbone.

Eisenhardt, K.M., 1989. Building Theories from Case Study Research. Acad. Manage. Rev. 14, 532–550. https://doi.org/10.2307/258557

El Haouat, Z., Essalih, S., Bennouna, F., Ramadany, M., Amegouz, D., 2023. The Contribution of an ERP System in an LCA Analysis: A Case Study, in: Lecture Notes in Networks and Systems. Springer Nature Switzerland, Cham, pp. 833–844. https://doi.org/10.1007/978-3-031-29857-8_83

EPD International, n.d. International EPD System | EPD International [WWW Document]. URL https://www.environdec.com/about-us/international-epd-system (accessed 7.22.25).

Essouid, W., Bouillass, G., Trebucq, S., Loubet, P., Sonnemann, G., 2024. UNVEILING THE SYNERGY: INTEGRATION OF TIME-DRIVEN ACTIVITY BASED COSTING WITH SOCIAL LIFE CYCLE ASSESSMENT, in: 9th International Conference of Social Life Cycle Assessment. Curitiba, Brazil.

Essouid, W., Loubet, P., Sonnemann, G., Trebucq, S., 2023. Integrating accounting data with Scope 3 emissions data for valorizing LCA results in a Life Cycle Management perspective. Presented at the LCM 2023, Lille.

Esteban-Amaro, R., Estelles-Miguel, S., Lengua, I., Yannou, B., Bouillass, G., 2024. The infinite framework: Enhancing sustainable development and circularity in value chains. Sustain. Dev. sd.3253. https://doi.org/10.1002/sd.3253

European Central Bank, 2023. Euro foreign exchange reference rates.

European Commission, 2025a. EU taxonomy for sustainable activities - European Commission [WWW Document]. URL https://finance.ec.europa.eu/sustainable-finance/tools-and-standards/eu-taxonomy-sustainable-activities_en (accessed 7.22.25).

European Commission, 2025b. Omnibus package - European Commission [WWW Document]. URL https://finance.ec.europa.eu/news/omnibus-package-2025-04-01_en (accessed 6.24.25).

European Commission, 2024. Regulation (EU) 2024/1781 of the European Parliament and of the Council of 13 June 2024 establishing a framework for the setting of ecodesign requirements for sustainable products, amending Directive (EU) 2020/1828 and Regulation (EU) 2023/1542 and repealing Directive 2009/125/EC (Text with EEA relevance). URL http://data.europa.eu/eli/reg/2024/1781/oj/eng (accessed 7.22.25).

European Commission, 2023a. Corporate sustainability reporting - EU Directive 2022/2464.

European Commission, 2023b. Proposal for a Directive on green claims [WWW Document]. URL https://environment.ec.europa.eu/publications/proposal-directive-green-claims_en (accessed 7.5.25).

European Commission, 2022. Règlement délégué - 2023/137 - FR - EUR-Lex.

European Commission, 2021. Commission Recommendation (EU) 2021/2279 of 15 December 2021 on the use of the Environmental Footprint methods to measure and communicate the life cycle environmental performance of products and organisations, OJ L.

European Commission, 2019a. Social procurement : Updated guidance and awareness-raising to make socially-responsible purchases.

European Commission, 2019b. The European Green Deal.

Fathi, M.R., Sobhani, S.M., Maleki, M.H., Jandaghi, G., 2021. Future study of textile industry in Iran using the MICMAC and soft operational research methods. foresight 23, 439–456. https://doi.org/10.1108/FS-02-2020-0017

Feschet, P., Loeillet, D., Macombe, C., Garrabé, M., 2010. Fruits and vegetables supply chains specificities and stakes as element of discussion on Social-LCA, in: 7th International Conference on Life Cycle Assessment in the Agri-Food Sector. Universita degli studi di Aldo Moro, Bari, Italy, p. 6 p.

Figge, F., Hahn, T., Schaltegger, S., Wagner, M., 2002. The Sustainability Balanced Scorecard – linking sustainability management to business strategy. Bus. Strategy Environ. 11, 269–284. https://doi.org/10.1002/bse.339

Finkbeiner, M., Schau, E.M., Lehmann, A., Traverso, M., 2010. Towards Life Cycle Sustainability Assessment. Sustainability 2, 3309–3322. https://doi.org/10.3390/su2103309

Finogenova, N., Bach, V., Berger, M., Finkbeiner, M., 2019. Hybrid approach for the evaluation of organizational indirect impacts (AVOID): combining product-related, process-based, and monetary-based methods. Int. J. Life Cycle Assess. 24, 1058–1074. https://doi.org/10.1007/s11367-018-1544-7

Forin, S., Martínez-Blanco, J., Finkbeiner, M., 2019. Facts and figures from road testing the guidance on organizational life cycle assessment. Int. J. Life Cycle Assess. 24, 866–880. https://doi.org/10.1007/s11367-018-1533-x

Forin, S., Martínez-Blanco, J., Finkbeiner, M., Inaba, A., 2017. Road testing organizational life cycle assessment around the world: Applications, experiences and lessons learned - Life Cycle Initiative. URL https://www.lifecycleinitiative.org/library/road-testing-organizational-life-cycle-assessment-around-the-world-applications-experiences-and-lessons-learned/ (accessed 9.18.24).

Fraser, I.J., Müller, M., Schwarzkopf, J., 2020. Dear supplier, how sustainable are you?: A multiple-case study analysis of a widespread tool for sustainable supply chain management. Sustain. Manag. Forum Nachhalt. 28, 127–149. https://doi.org/10.1007/s00550-020-00507-z

French Directorate for Legal and Administrative Information, 2025. À quoi correspond le code APE (code NAF) ? | Entreprendre.Service-Public.fr.

French Directorate for Legal and Administrative Information, 2024. Quels sont les numéros d'identification d'une entreprise ?

Gamarra, A.R., Lechón, Y., Banacloche, S., Corona, B., de Andrés, J.M., 2023. A comparison and methodological proposal for hybrid approaches to quantify environmental impacts: A case study for renewable energies. Sci. Total Environ. 867, 161502. https://doi.org/10.1016/j.scitotenv.2023.161502

García-Alaminos, Á., Gilles, E., Monsalve, F., Zafrilla, J., 2022. Measuring a university's environmental performance: A standardized proposal for carbon footprint assessment. J. Clean. Prod. 357, 131783. https://doi.org/10.1016/j.jclepro.2022.131783

Geissdoerfer, M., Savaget, P., Bocken, N.M.P., Hultink, E.J., 2017. The Circular Economy – A new sustainability paradigm? J. Clean. Prod. 143, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

Georgiou, E., Raffin, M., Colquhoun, K., Borrion, A., Campos, L.C., 2019. The significance of measuring embodied carbon dioxide equivalent in water sector infrastructure. J. Clean. Prod. 216, 268–276. https://doi.org/10.1016/j.jclepro.2019.01.014

Gerged, A.M., Matthews, L., Elheddad, M., 2021. Mandatory disclosure, greenhouse gas emissions and the cost of equity capital: UK evidence of a U-shaped relationship. Bus. Strategy Environ. 30, 908–930. https://doi.org/10.1002/bse.2661

Ghisellini, P., Passaro, R., Ulgiati, S., 2023. Environmental and Social Life Cycle Assessment of Waste Electrical and Electronic Equipment Management in Italy According to EU Directives. Environments 10, 106. https://doi.org/10.3390/environments10070106

Ghosh, T., Bakshi, B.R., 2020. Designing hybrid life cycle assessment models based on uncertainty and complexity. Int. J. Life Cycle Assess. 25, 2290–2308. https://doi.org/10.1007/s11367-020-01826-5

Gijo, E. v., Scaria, J., 2010. Reducing rejection and rework by application of Six Sigma methodology in manufacturing process. Int. J. Six Sigma Compet. Advant. 6, 77–90. https://doi.org/10.1504/IJSSCA.2010.034857

Giljum, S., Wieland, H., Lutter, S., Eisenmenger, N., Schandl, H., Owen, A., 2019. The impacts of data deviations between MRIO models on material footprints: A comparison of EXIOBASE, Eora, and ICIO. J. Ind. Ecol. 23, 946. https://doi.org/10.1111/jiec.12833

Glover, 2025. What Is Artificial Intelligence (AI)? Built In. URL https://builtin.com/artificial-intelligence (accessed 7.25.25).

Godet, M., 2007. Manuel de prospective stratégique - Tome 1 - 3ème édition - Une indiscipline intellectuelle. Dunod.

Gómez, N., Cadarso, M.-Á., Monsalve, F., 2016. Carbon footprint of a university in a multiregional model: the case of the University of Castilla-La Mancha. J. Clean. Prod., Research on sustainable cleaner production and sustainable energy options 138, 119–130. https://doi.org/10.1016/j.jclepro.2016.06.009

GRI, 2023. GRI standards 2023: Sustainability reporting framework., Global Reporting Initiative.

Guan, J., Zhang, Z., Chu, C., 2016. Quantification of building embodied energy in China using an input–output-based hybrid LCA model. Energy Build. 110, 443–452. https://doi.org/10.1016/j.enbuild.2015.11.032

Guinée, J.B., Heijungs, R., Huppes, G., Zamagni, A., Masoni, P., Buonamici, R., Ekvall, T., Rydberg, T., 2011. Life Cycle Assessment: Past, Present, and Future. Environ. Sci. Technol. 45, 90–96. https://doi.org/10.1021/es101316v

Gunaratne, K., 2025. Master's programme in Supply Management.

Hagenaars, R.H., Heijungs, R., Tukker, A., Wang, R., 2025. Hybrid LCA for sustainable transitions: principles, applications, and prospects. Renew. Sustain. Energy Rev. 212, 115443. https://doi.org/10.1016/j.rser.2025.115443

Hahn, R., Kühnen, M., 2013. Determinants of sustainability reporting: a review of results, trends, theory, and opportunities in an expanding field of research. J. Clean. Prod. 59, 5–21. https://doi.org/10.1016/j.jclepro.2013.07.005

Hamed, A., Ciroth, A., 2024. soca v3 add-on – Adding social impact information to ecoinvent Description of methodology to map social impact information from PSILCA 3.1.1 to ecoinvent 3.10. GreenDelta GmbH.

Harasymchuk, I., Kočí, V., Hájková, M., Srb, M., Salová, N., Sýkora, P., 2024. Water supply and sewerage: Path to Net Zero Organizational Emissions. J. Sustain. Dev. Energy Water Environ. Syst. [12], [1]-[20].

Harmens, R., Goedkoop, M., Alvarenga, R.A.F., Lieselot Boone, Martinez, E.C., Zanchi, L., Zamagni, A., Sonderegger, T., Ruiz, E.M., Saling, P., Cordella, M., 2022. ORIENTING - D1.2 Critical evaluation of social approaches. https://doi.org/10.13140/RG.2.2.16478.31042

Heijungs, R., Suh, S., 2002. The Computational Structure of Life Cycle Assessment. Springer Science & Business Media.

Heijungs, R., Yang, Y., Park, H.-S., 2022. A or I-A? Unifying the computational structures of process- and IO-based LCA for clarity and consistency. J. Ind. Ecol. 26, 1824–1836. https://doi.org/10.1111/jiec.13323

Helo, P., Mayanti, B., Bejarano, R., Sundman, C., 2024. Sustainable supply chains – Managing environmental impact data on product platforms. Int. J. Prod. Econ. 270, 109160. https://doi.org/10.1016/j.ijpe.2024.109160

Hendrickson, C.T., Lave, L.B., Matthews, H.S., 2006. Environmental Life Cycle Assessment of Goods and Services: An Input-Output Approach. Routledge, New York. https://doi.org/10.4324/9781936331383

Herth, A., Blok, K., 2023. Quantifying universities' direct and indirect carbon emissions – the case of Delft University of Technology. Int. J. Sustain. High. Educ. 24, 21–52. https://doi.org/10.1108/IJSHE-04-2022-0121

Hertwich, E.G., Peters, G.P., 2009. Carbon Footprint of Nations: A Global, Trade-Linked Analysis. Environ. Sci. Technol. 43, 6414–6420. https://doi.org/10.1021/es803496a

Herzog, H.W., 1973. An environmental assessment of future production-related technological change: 1970–2000 (An input-output approach). Technol. Forecast. Soc. Change 5, 75–90. https://doi.org/10.1016/0040-1625(73)90020-6

Hettler, M., Graf-Vlachy, L., 2024. Corporate scope 3 carbon emission reporting as an enabler of supply chain decarbonization: A systematic review and comprehensive research agenda. Bus. Strategy Environ. 33, 263–282. https://doi.org/10.1002/bse.3486

Hinterhuber, A., Khan, O., 2025. What drives sustainable procurement? Insights from the theory of planned behavior. Int. J. Oper. Prod. Manag. 45, 28–52. https://doi.org/10.1108/IJOPM-02-2024-0164

Hoozze, S., Hansen, S.C., 2014. A Comparison of Activity-Based Costing and Time-Driven Activity-Based Costing. SSRN Electron. J. https://doi.org/10.2139/ssrn.2489118

Hu, H., Jiang, S., Goswami, S.S., Zhao, Y., 2024. Fuzzy Integrated Delphi-ISM-MICMAC Hybrid Multi-Criteria Approach to Optimize the Artificial Intelligence (AI) Factors Influencing Cost Management in Civil Engineering. Information 15, 280. https://doi.org/10.3390/info15050280

Huang, Q., Sun, Y., Guo, Q., Li, Q., Zhang, Y., Li, X., Wang, L., 2025. Social life cycle assessment and its methodological challenges: A bibliometric and content analysis. J. Ind. Ecol. 29, 264–278. https://doi.org/10.1111/jiec.13605

Huang, Y.A., Lenzen, M., Weber, C.L., Murray, J., Matthews, H.S., 2009a. THE ROLE OF INPUT–OUTPUT ANALYSIS FOR THE SCREENING OF CORPORATE CARBON FOOTPRINTS. Econ. Syst. Res. 21, 217–242. https://doi.org/10.1080/09535310903541348

Huang, Y.A., Weber, C.L., Matthews, H.S., 2009b. Categorization of Scope 3 Emissions for Streamlined Enterprise Carbon Footprinting. Environ. Sci. Technol. 43, 8509–8515. https://doi.org/10.1021/es901643a

Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., G. Stam, Verones, F., M.D.M. Vieira, A. Hollander, M. Zijp, R. van Zelm, 2016. ReCiPe 2016 A harmonized life cycle impact assessment method at midpoint and endpoint level Report I: Characterization (No. RIVM Report 2016-0104).

Iacobuţă, G.I., Höhne, N., van Soest, H.L., Leemans, R., 2021. Transitioning to Low-Carbon Economies under the 2030 Agenda: Minimizing Trade-Offs and Enhancing Co-Benefits of Climate-Change Action for the SDGs. Sustainability 13, 10774. https://doi.org/10.3390/su131910774

Ibrahim, M., Auwal1, B.M., Balarabe, A.S., Isa, I.A., 2024. Sustainability Reporting Frameworks A Comparative Analysis of Reporting Standards and their Implications for Accounting and Reporting. Int. J. Account. Finance Adm. Res. 1, 32–47.

Imai, M., 1986. Kaizen The Key to Japan's Competitive Success, Scientific Research Publishing. ed, McGraw-Hill Education, New York.

Infociment, 2018. Classes d'exposition du béton norme NF - Composition des bétons.

INIES, n.d. FDES (Produits de construction). Inies. URL https://www.inies.fr/inies-et-ses-donnees/fdes-produits-de-construction/ (accessed 7.22.25).

INSEE, 2025. L'essentiel sur... l'inflation | Insee.

INSEE, 2022. Émissions de gaz à effet de serre et empreinte carbone de la France en 2023 − Comptes nationaux | Insee.

INSEE, 2015. Definition - French classification of products / CPF / CPF REv 2.1.

Iofrida, N., Saez de Bikuña Salinas, K., Mistretta, M., Falcone, G., Spada, E., Gulisano, G., De Luca, A.I., 2024. Social life cycle assessment of garments production using the psychosocial risk factors impact pathway. J. Clean. Prod. 458, 142448. https://doi.org/10.1016/j.jclepro.2024.142448

Islam, S., Ponnambalam, S.G., Lam, H.L., 2016. Review on life cycle inventory: methods, examples and applications. J. Clean. Prod., PRES'15: Cleaner energy planning, management and technologies 136, 266–278. https://doi.org/10.1016/j.jclepro.2016.05.144

ISO, 2006. ISO 14025:2006 Environmental labels and declarations — Type III environmental declarations — Principles and procedures.

ISO 14040, 2006. ISO 14040:2006 Environmental Management – Life Cycle Assessment – Principles and Framework.

ISO 14044, 2006. ISO 14044:2006 Environmental management — Life cycle assessment — Requirements and guidelines.

ISO 14064, 2018. Specification with guidance at the organization level for quantification and reporting of greenhouse gas emissions and removals.

ISO 14072, 2024. Environmental management - Life cycle assessment - Requirements and guidelines for organizational life cycle assessment.

ISO 14075:2024 [WWW Document], 2024. . ISO. URL https://www.iso.org/standard/61118.html (accessed 1.13.25).

ISO 20400, 2017. Sustainable procurement — Guidance.

ISO 26000, 2010. ISO 26000:2010(en), Guidance on social responsibility.

Issa Zadeh, S.B., López Gutiérrez, J.S., Esteban, M.D., Fernández-Sánchez, G., Garay-Rondero, C.L., 2023. Scope of the Literature on Efforts to Reduce the Carbon Footprint of Seaports. Sustainability 15, 8558. https://doi.org/10.3390/su15118558

ISSB, 2023. IFRS - IFRS S1 General Requirements for Disclosure of Sustainability-related Financial Information, International Sustainability Standards Board.

Jakobsen, A.M.S.Ø., Tambo, T., 2025. Current state of sustainability representation product lifecycle management systems and future Perspectives: A comparative evaluation. Clean. Logist. Supply Chain 16, 100229. https://doi.org/10.1016/j.clscn.2025.100229

Jemal, S., Schmidt, A., 2025. The Omnibus Simplification Package: explained. Normative. URL https://normative.io/insight/the-omnibus-simplification-package-explained/ (accessed 7.26.25).

Jenny, J., 1997. Methodes Et Pratiques Formalisees D'Analyse De Contenu Et De Discours Dans La Recherche Sociologique Francaise Contemporaine. Etat Des Lieux Et Essai De Classification. Bull. Sociol. Methodol. Méthodologie Sociol. 54, 64–122. https://doi.org/10.1177/075910639705400104

Jiang, Q., Li, T., Liu, Z., Zhang, H., Ren, K., 2014. Life Cycle Assessment of an Engine with Input-Output Based Hybrid Analysis Method. J. Clean. Prod. 78, 131–138. https://doi.org/10.1016/j.jclepro.2014.04.003

Jones, M.J., 2003. Accounting for biodiversity: operationalising environmental accounting. Account. Audit. Account. J. 16, 762–789. https://doi.org/10.1108/09513570310505961

Jørgensen, A., Le Bocq, A., Nazarkina, L., Hauschild, M., 2008. Methodologies for social life cycle assessment. Int. J. Life Cycle Assess. 13, 96–103. https://doi.org/10.1065/lca2007.11.367

Joshi, S., 1999. Product Environmental Life-Cycle Assessment Using Input-Output Techniques. J. Ind. Ecol. 3, 95–120.

Jourdaine, M., 2020. Mise en place d'une comptabilité analytique environnementale mobilisant l'analyse du cycle de vie (ACV) et l'activity-based costing (ABC) : application au cas viti-vinicole (phdthesis). Université de Bordeaux.

Jourdaine, M., Loubet, P., Sonnemann, G., Trébucq, S., 2021. The ABC-LCA method for the integration of activity-based costing and life cycle assessment. Bus. Strategy Environ. 30, 1735–1750. https://doi.org/10.1002/bse.2712

Jungbluth, N., Keller, R., König, A., 2016. ONE TWO WE—life cycle management in canteens together with suppliers, customers and guests. Int. J. Life Cycle Assess. 21, 646–653. https://doi.org/10.1007/s11367-015-0982-8

Kalverkamp, M., Helmers, E., Pehlken, A., 2020. Impacts of life cycle inventory databases on life cycle assessments: A review by means of a drivetrain case study. J. Clean. Prod. 269, 121329. https://doi.org/10.1016/j.jclepro.2020.121329

Kaplan, R.S., Anderson, S.R., 2007. Time-driven activity-based costing: a simpler and more powerful path to higher profits, 3. [Dr.]. ed. Harvard Business School Press, Boston, Mass.

Kaplan, R.S., Anderson, S.R., 2004. Time-Driven Activity- Based Costing.

Kaplan, R.S., Norton, D.P., 1996. strategic learning & the balanced scorecard. Strategy Leadersh. 24, 18–24. https://doi.org/10.1108/eb054566

Kaplan, R.S., Ramanna, K., 2021. Accounting for Climate Change. Harv. Bus. Rev.

Karlewski, H., Lehmann, A., Ruhland, K., Finkbeiner, M., 2019. A Practical Approach for Social Life Cycle Assessment in the Automotive Industry. Resources 8, 146. https://doi.org/10.3390/resources8030146

Keil, M., 2023. The greenhouse gas emissions of a German hospital - A case study of an easy-to-use approach based on financial data. Clean. Environ. Syst. 11, 100140. https://doi.org/10.1016/j.cesys.2023.100140

Kelvin, Lord, 1891. Electrical Units of Measurement, a Lecture Given on 3 May 1883, Published in the Book "Popular Lectures and Addresses, Volume 1.

Kenton, W., 2024. Activity-Based Costing (ABC): Method and Advantages Defined with Example. Investopedia. URL https://www.investopedia.com/terms/a/abc.asp (accessed 7.25.25).

Kim, M., Chai, S., 2017. Implementing Environmental Practices for Accomplishing Sustainable Green Supply Chain Management. Sustainability 9, 1192. https://doi.org/10.3390/su9071192

King, C.W., Zarnikau, J., Henshaw, P., 2010. Defining a standard measure for whole system eroi combining economic "top-down" and lca "bottom-up" accounting. Presented at the ASME 2010 4th International Conference on Energy Sustainability, ES 2010, pp. 969–978. https://doi.org/10.1115/ES2010-90414

Kitzes, J., 2013. An Introduction to Environmentally-Extended Input-Output Analysis. Resources 2, 489–503. https://doi.org/10.3390/resources2040489

Kjaer, L.L., Høst-Madsen, N.K., Schmidt, J.H., McAloone, T.C., 2015. Application of Environmental Input-Output Analysis for Corporate and Product Environmental Footprints—Learnings from Three Cases. Sustainability 7, 11438–11461. https://doi.org/10.3390/su70911438

Klaaßen, L., Stoll, C., 2021. Harmonizing corporate carbon footprints. Nat. Commun. 12, 6149. https://doi.org/10.1038/s41467-021-26349-x

Klymenko, O., Lillebrygfjeld Halse, L., Jæger, B., 2021. The Enabling Role of Digital Technologies in Sustainability Accounting: Findings from Norwegian Manufacturing Companies. Systems 9, 33. https://doi.org/10.3390/systems9020033

Koch, P., Salou, T., Auberger, J., Colomb, V., Galland, V., Perret, S., Tailleur, A., Willmann, S., Cornelus, M., 2022. AGRIBALYSE® : RAPPORT METHODOLOGIQUE, VOLET AGRICULTURE.

Köck, B., Friedl, A., Serna Loaiza, S., Wukovits, W., Mihalyi-Schneider, B., 2023. Automation of Life Cycle Assessment—A Critical Review of Developments in the Field of Life Cycle Inventory Analysis. Sustainability 15, 5531. https://doi.org/10.3390/su15065531

Kokubo Roche, A., Tsalidis, G.A., Blanco, C.F., Dias, D.F.C., Posada, J.A., 2025. Generic and site-specific social life cycle assessment of municipal wastewater treatment systems in Spain: challenges and limitations of the method when applied to resource recovery systems. Int. J. Life Cycle Assess. 30, 1480–1504. https://doi.org/10.1007/s11367-024-02370-2

Kronenberg, T., 2010. What can post-Keynesian input-output models tell us about social sustainability?

Larsen, V.G., Tollin, N., Sattrup, P.A., Birkved, M., Holmboe, T., 2022. What are the challenges in assessing circular economy for the built environment? *A literature review on integrating LCA,*

LCC and S-LCA in life cycle sustainability assessment, LCSA. J. Build. Eng. 50, 104203. https://doi.org/10.1016/j.jobe.2022.104203

Lastauskas, P., Ding, Z., Douch, M., 2024. The Heterogeneous Impacts of Firm Upgrading on Energy Intensity. IMF.

Laurent, A., Weidema, B.P., Bare, J., Liao, X., Maia de Souza, D., Pizzol, M., Sala, S., Schreiber, H., Thonemann, N., Verones, F., 2020. Methodological review and detailed guidance for the life cycle interpretation phase. J. Ind. Ecol. 24, 986–1003. https://doi.org/10.1111/jiec.13012

Lawson, D., 2024. Spend-Based Carbon Accounting: A Practical Approach. URL https://www.atlasmetrics.io/blog/simplifying-carbon-accounting-with-the-spend-based-method (accessed 7.26.25).

Le Den, X., Steinmann, J., Röck, M., Birgisdottir, H., Horup, L.H., Tozan, B., Sørensen, A., 2022. Towards embodied carbon benchmarks for buildings in Europe - Summary report. Zenodo. https://doi.org/10.5281/zenodo.6397514

Lee, K., Cheong, I., 2011. Measuring a carbon footprint and environmental practice: the case of Hyundai Motors Co. (HMC). Ind. Manag. Data Syst. 111, 961–978. https://doi.org/10.1108/02635571111144991

Lee, K.-H., 2011. Integrating carbon footprint into supply chain management: the case of Hyundai Motor Company (HMC) in the automobile industry. J. Clean. Prod. 19, 1216–1223. https://doi.org/10.1016/j.jclepro.2011.03.010

Lee, S., 2025. NLP in Environmental Informatics. URL https://www.numberanalytics.com/blog/nlp-in-environmental-informatics-ultimate-guide (accessed 7.25.25).

Lehmann, J., 2023. Integration of Social Life Cycle Assessment as a tool for evaluation and decision-making in the design phase of offshore wind farm projects in France (phdthesis). Université Paris sciences et lettres.

Leiminger, F., 2021. Spend-based carbon accounting – A useful or oversimplified methodology? DFGE - Inst. Energy Ecol. Econ. URL https://dfge.de/spend-based-carbon-accounting/ (accessed 7.26.25).

Lejeune, C., 2017. Chapitre 9. Analyser les contenus, les discours ou les vécus ? À chaque méthode ses logiciels !, in: Les méthodes qualitatives en psychologie et sciences humaines de la santé. Dunod, pp. 203–224. https://doi.org/10.3917/dunod.santi.2017.01.0203

Lenzen, M., 2000. Errors in Conventional and Input-Output—based Life—Cycle Inventories. J. Ind. Ecol. 4, 127–148.

Lenzen, M., Crawford, R., 2009. The Path Exchange Method for Hybrid LCA. Environ. Sci. Technol. 43, 8251–8256. https://doi.org/10.1021/es902090z

Lenzen, M., Geschke, A., Abd Rahman, M.D., Xiao, Y., Fry, J., Reyes, R., Dietzenbacher, E., Inomata, S., Kanemoto, K., Los, B., Moran, D., Schulte in den Bäumen, H., Tukker, A., Walmsley, T., Wiedmann, T., Wood, R., Yamano, N., 2017. The Global MRIO Lab – charting the world economy. Econ. Syst. Res. 29, 158–186. https://doi.org/10.1080/09535314.2017.1301887

Lenzen, M., Moran, D., Kanemoto, K., Geschke, A., 2013. Building Eora: A Global Multi-Region Input–Output Database at High Country and Sector Resolution. Econ. Syst. Res. 25, 20–49. https://doi.org/10.1080/09535314.2013.769938

Leontief, W., 1974. Sructure of the World Economy: Outline of a Simple Input-Output Formulation. Am. Econ. Rev. 64, 823–834.

Leontief, W., Ford, D., 1972. Air pollution and the economic structure : empirical results of input-output computations. Input-Output Tech. Proc. Fifth Int. Conf. Input-Output Tech. Geneva January 1971, Input-output techniques : proceedings of the Fifth International Conference on Input-Output Techniques ; Geneva, January, 1971. - Amsterdam [u.a.] : North-Holland Publ. Co., ISBN 0-7204-3064-X. - 1972, p. 9-30.

Leontief, W.W., 1941. The structure of American economy, 1919-1929 : an empirical application of equilibrium analysis. Harvard university press.

Li, W.Y., Chersoni, E., Ngai, C.S.B., 2024. Evaluating Multilingual Language Models for Cross-Lingual ESG Issue Identification, in: Chen, C.-C., Liu, X., Hahn, U., Nourbakhsh, A., Ma, Z., Smiley, C., Hoste, V., Das, S.R., Li, M., Ghassemi, M., Huang, H.-H., Takamura, H., Chen, H.-H. (Eds.), Proceedings of the Joint Workshop of the 7th Financial Technology and Natural Language Processing, the 5th Knowledge Discovery from Unstructured Data in Financial Services, and the 4th Workshop on Economics and Natural Language Processing. Presented at the FinNLP 2024, Association for Computational Linguistics, Torino, Italia, pp. 50–58.

Liang, S., Feng, T., Qu, S., Chiu, A.S.F., Jia, X., Xu, M., 2017. Developing the Chinese Environmentally Extended Input-Output (CEEIO) Database. J. Ind. Ecol. 21, 953–965. https://doi.org/10.1111/jiec.12477

Lintukangas, K., Arminen, H., Kähkönen, A.-K., Karttunen, E., 2023. Determinants of Supply Chain Engagement in Carbon Management. J. Bus. Ethics 186, 87–104. https://doi.org/10.1007/s10551-022-05199-7

Liou, M., 2023. Process Accuracy and Precision Monitoring, Evaluation and Improvement Model.

Lohar, P., Xie, G., Gallagher, D., Way, A., 2023. Building Neural Machine Translation Systems for Multilingual Participatory Spaces. Analytics 2, 393–409. https://doi.org/10.3390/analytics2020022

Lo-Iacono-Ferreira, V.G., Torregrosa-López, J.I., Capuz-Rizo, S.F., 2017. Organizational life cycle assessment: suitability for higher education institutions with environmental management systems. Int. J. Life Cycle Assess. 22, 1928–1943. https://doi.org/10.1007/s11367-017-1289-8

Loreti, C.P., Obbagy, J.E., Foster, S.A., 2001. An Overview of Greenhouse Gas Emissions Verification Issues. Center for Climate and Energy Solutions.

Loubet, P., 2023. Habilitation à diriger des recherches : Développements méthodologiques et dissémination de l'Analyse du Cycle de Vie pour accompagner la transition écologique de la recherche et de l'industrie. https://doi.org/10.13140/RG.2.2.10268.40320

Lu, X., 2024. Influence of financial accounting information transparency on supply chain financial decision-making. Heliyon 10, e33113. https://doi.org/10.1016/j.heliyon.2024.e33113

Lucarelli, C., Mazzoli, C., Rancan, M., Severini, S., 2023. The impact of eu taxonomy on corporate investments. J. Financ. Manag. Mark. Inst. 11, 2350004. https://doi.org/10.1142/S2282717X23500044

Lueddeckens, S., Saling, P., Guenther, E., 2022. Discounting and life cycle assessment: a distorting measure in assessments, a reasonable instrument for decisions. Int. J. Environ. Sci. Technol. 19, 2961–2972. https://doi.org/10.1007/s13762-021-03426-8

Lyons, M., Adjali, I., Collings, D., Jensen, K., 2003. Complex Systems Models for Strategic Decision Making. BT Technol. J. 21, 11–27. https://doi.org/10.1023/A:1024419706667

Macombe, C., Leskinen, P., Feschet, P., Antikainen, R., 2013. Social life cycle assessment of biodiesel production at three levels: a literature review and development needs. J. Clean. Prod. 52, 205–216. https://doi.org/10.1016/j.jclepro.2013.03.026

Mahmoudian, F., Lu, J., Yu, D., Nazari, J.A., Herremans, I.M., 2021. Inter-and intra-organizational stakeholder arrangements in carbon management accounting. Br. Account. Rev. 53, 100933. https://doi.org/10.1016/j.bar.2020.100933

Mähönen, M., Martini, L., Gardiner, J., Lehtilä, S., Görlach, B., 2023. Public Procurement for Climate Neutrality – a transformative policy instrument?

Maister, K., Di Noi, C., Ciroth, A., Srocka, M., 2020. PSILCA v.3. PSILCA Doc.

Malik, A., Lenzen, M., Ralph, P.J., Tamburic, B., 2015. Hybrid life-cycle assessment of algal biofuel production. Bioresour. Technol., Advances in biofuels and chemicals from algae 184, 436–443. https://doi.org/10.1016/j.biortech.2014.10.132

Manzardo, A., Loss, A., Jingzheng, R., Zuliani, F., Scipioni, A., 2018. Definition and application of activity portfolio and control/influence approaches in organizational life cycle assessment. J. Clean. Prod. 184, 264–273. https://doi.org/10.1016/j.jclepro.2018.02.262

Marinho Neto, H.F., Agostinho, F., Almeida, C.M.V.B., Moreno García, R.R., Giannetti, B.F., 2018. Activity-Based Costing Using Multicriteria Drivers: An Accounting Proposal to Boost Companies Toward Sustainability. Front. Energy Res. 6. https://doi.org/10.3389/fenrg.2018.00036

Martinez, S., Delgado, M. del M., Martinez Marin, R., Alvarez, S., 2019. Organization Environmental Footprint through Input-Output Analysis: A Case Study in the Construction Sector. J. Ind. Ecol. 23, 879–892. https://doi.org/10.1111/jiec.12827

Martinez, S., Marchamalo, M., Alvarez, S., 2018. Organization environmental footprint applying a multi-regional input-output analysis: A case study of a wood parquet company in Spain. Sci. Total Environ. 618, 7–14. https://doi.org/10.1016/j.scitotenv.2017.10.306

Marx, H., Forin, S., Finkbeiner, M., 2020. Organizational Life Cycle Assessment of a Service Providing SME for Renewable Energy Projects (PV and Wind) in the United Kingdom. Sustainability 12, 4475. https://doi.org/10.3390/su12114475

Matas, S., Oplotnik, Ž.J., Jagrič, T., 2025. Can We Have Both? The Challenges of Efficiency Outcomes in a Public Procurement System and Reaching the Strategic Goals of Procurement. Sustainability 17, 2475. https://doi.org/10.3390/su17062475

Max, 2025. Use an LCA to meet these 5 standards and legislations. Hedgehog. URL https://www.hhc.earth/knowledge-base/articles/use-an-lca-to-meet-these-5-standards-and-legislations (accessed 7.26.25).

Maxime Agez, 2024. CIRAIG/OpenIO-Canada: v2.9. https://doi.org/10.5281/ZENODO.10971810

McElroy, M.W., 2015. Chapter 5: The Social Footprint Method, in: The Sustainability Practitioner's Guide to Social Analysis and Assessment.

McLean, R.S., 2019. A practical continuous improvement implementation framework for UK manufacturing companies (Thesis). Social Sciences.

McMillan, A., 2025. BCG: Making the Supply Chain More Cost Efficient [WWW Document]. URL https://supplychaindigital.com/supply-chain-risk-management/bcg-making-supply-chain-more-cost-efficient (accessed 3.20.25).

Meinrenken, C.J., Chen, D., Esparza, R.A., Iyer, V., Paridis, S.P., Prasad, A., Whillas, E., 2020. Carbon emissions embodied in product value chains and the role of Life Cycle Assessment in curbing them. Sci. Rep. 10, 6184. https://doi.org/10.1038/s41598-020-62030-x

Mena, C., Humphries, A., Choi, T.Y., 2013. Toward a Theory of Multi-Tier Supply Chain Management. J. Supply Chain Manag. 49, 58–77. https://doi.org/10.1111/jscm.12003

Mikolov, T., Chen, K., Corrado, G., Dean, J., 2013. Efficient Estimation of Word Representations in Vector Space. https://doi.org/10.48550/arXiv.1301.3781

Milne, M.J., 1996. On sustainability; the environment and management accounting. Manag. Account. Res. 7, 135–161. https://doi.org/10.1006/mare.1996.0007

Montemayor, E., Andrade, E.P., Bonmatí, A., Antón, A., 2022. Critical analysis of life cycle inventory datasets for organic crop production systems. Int. J. Life Cycle Assess. 27, 543–563. https://doi.org/10.1007/s11367-022-02044-x

Montoya-Torres, J.R., Gutierrez-Franco, E., Blanco, E.E., 2015. Conceptual framework for measuring carbon footprint in supply chains. Prod. Plan. Control 26, 265–279. https://doi.org/10.1080/09537287.2014.894215

Moshood, T.D., Rotimi, J.O.B., Rotimi, F.E., 2024. Combating Greenwashing of Construction Products in New Zealand and Australia: A Critical Analysis of Environmental Product Declarations. Sustainability 16, 9671. https://doi.org/10.3390/su16229671

Nakamura, S., 2023. A Practical Guide to Industrial Ecology by Input-Output Analysis: Matrix-Based Calculus of Sustainability. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-031-43684-0

Nakamura, S., 1999. An interindustry approach to analyzing economic and environmental effects of the recycling of waste. Ecol. Econ. 28, 133–145. https://doi.org/10.1016/S0921-8009(98)00031-7

Namdar, J., Modi, S., Blackhurst, J., 2025. Diversify or Concentrate? Supply Chain Responses to Policy Uncertainty. J. Supply Chain Manag. 61, 62–82. https://doi.org/10.1111/jscm.12336

Naro, G., Rambaud, A., 2023. Pour une refondation des pratiques et théories comptables : vers une exigence de soutenabilité forte. Comptab. Contrô Audit 29, 7–17. https://doi.org/10.3917/cca.294.0007

Nazara, S., Guo, D., J.D. Hewings, G., Dridi, C., 2003. PyIO – REAL.

Nazlabadi, E., Maknoon, R., Reza Alavi Moghaddam, M., Daigger, G.T., 2023. A novel MICMAC approach for cross impact analysis with application to urban water/wastewater management. Expert Syst. Appl. 230, 120667. https://doi.org/10.1016/j.eswa.2023.120667

Neppach, S., Nunes, K.R.A., Schebek, L., 2017. Organizational Environmental Footprint in German construction companies. J. Clean. Prod., Cleaner production towards a sustainable transition 142, 78–86. https://doi.org/10.1016/j.jclepro.2016.05.065

Nicholls, D., Barnes, F., Acrea, F., Chen, C., Buluç, L.Y., Parker, M.M., 2015. Top-Down and Bottom-Up Approaches to Greenhouse Gas Inventory Methods. United States Department of Agriculture.

Nordman, M., Lassen, A.D., Christensen, L.M., Trolle, E., 2024. Tracking progress toward a climate-friendly public food service strategy: assessing nutritional quality and carbon footprint changes in childcare centers. Nutr. J. 23, 13. https://doi.org/10.1186/s12937-024-00917-5

Norris, C., Norris, G., Aulisio, D., 2014. Efficient Assessment of Social Hotspots in the Supply Chains of 100 Product Categories Using the Social Hotspots Database. Sustainability 6, 6973–6984. https://doi.org/10.3390/su6106973

Northmore, L., Hudson, M.D., 2022. Digital environmental impact assessment: An exploration of emerging digital approaches for non-technical reports. Environ. Impact Assess. Rev. 92, 106689. https://doi.org/10.1016/j.eiar.2021.106689

Notarnicola, B., Tassielli, G., Renzulli, P.A., Chirulli, P., 2023. Organizational life cycle assessment of a corporate group. Clean. Environ. Syst. 9, 100125. https://doi.org/10.1016/j.cesys.2023.100125

Oberschelp, C., Hellweg, S., Bradford, E., Pfister, S., Huo, J., Wang, Z., 2023. Poor data and outdated methods sabotage the decarbonization efforts of the chemical industry. https://doi.org/10.26434/chemrxiv-2023-8c86t

Olanrewaju, O.I., Enegbuma, W.I., Donn, M., 2025. Environmental product declaration development and utilisation for whole building life cycle Assessment: Challenges and data quality assurance indicators. J. Clean. Prod. 521, 146170. https://doi.org/10.1016/j.jclepro.2025.146170

Oliveira, F.B. de, Nordelöf, A., Sandén, B.A., Widerberg, A., Tillman, A.-M., 2022. Exploring automotive supplier data in life cycle assessment – Precision versus workload. Transp. Res. Part Transp. Environ. 105, 103247. https://doi.org/10.1016/j.trd.2022.103247

Oliveira, F.S. de, Neto, O.R. de M., Oyadomari, J.C.T., 2025. Accounts That Matter: A Systematic Review of Accounting's Role in Integrating Sustainability Into Organizational Performance. Account. Finance Gov. Rev. 34. https://doi.org/10.52399/001c.134047

Omran, N., Sharaai, A.H., Hashim, A.H., 2021. Visualization of the Sustainability Level of Crude Palm Oil Production: A Life Cycle Approach. Sustainability 13, 1607. https://doi.org/10.3390/su13041607

Ortiz-Cea, V., Dote-Pardo, J., Geldres-Weiss, V.V., Peña-Acuña, V., 2025. The Role of Activity-Based Costing in Reducing Environmental Impact: A Systematic Literature Review. Sustainability 17, 1275. https://doi.org/10.3390/su17031275

Ostojic, S., Simone, L., Edler, M., Traverso, M., 2024. How Practically Applicable Are the EU Taxonomy Criteria for Corporates?—An Analysis for the Electrical Industry. Sustainability 16, 1575. https://doi.org/10.3390/su16041575

Ostojic, S., Traverso, M., 2024. Application of Life Cycle Sustainability Assessment in the automotive sector – A systematic literature review. Sustain. Prod. Consum. 47, 105–127. https://doi.org/10.1016/j.spc.2024.03.033

Ozawa-Meida, L., Brockway, P., Letten, K., Davies, J., Fleming, P., 2013. Measuring carbon performance in a UK University through a consumption-based carbon footprint: De Montfort University case study. J. Clean. Prod., Sustainability management beyond corporate boundaries 56, 185–198. https://doi.org/10.1016/j.jclepro.2011.09.028

Pacioli, L., 1494. Summa de arithmetica, geometria, de proportioni et de proportionalita.

Paepe, M.D., Jeanneau, L., Mariette, J., Aumont, O., Estevez-Torres, A., 2023. Purchases dominate the carbon footprint of research laboratories. https://doi.org/10.1101/2023.04.04.535626

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ n71. https://doi.org/10.1136/bmj.n71

Palma-Rojas, S., Nogueira, J., 2015. Environmental and economic hybrid life cycle assessment of bagasse-derived ethanol produced in Brazil. Int. J. Life Cycle Assess. 22. https://doi.org/10.1007/s11367-015-0892-9

Paolone, F., Sardi, A., Sorano, E., Ferraris, A., 2020. Integrated processing of sustainability accounting reports: a multi-utility company case study. Meditari Account. Res. 29, 985–1004. https://doi.org/10.1108/MEDAR-01-2020-0667

Papafloratos, T., Pantazi, T., 2025. A Systematic Review of the Effects of Mandatory Corporate Sustainability Reporting. Sustainability 17, 5336. https://doi.org/10.3390/su17125336

Patil, V., Tan, T., Rispens, S., Dabadghao, S., Demerouti, E., 2022. Supplier sustainability: A comprehensive review and future research directions. Sustain. Manuf. Serv. Econ. 1, 100003. https://doi.org/10.1016/j.smse.2022.100003

Pedersen, E., Remmen, A., 2022. Challenges with product environmental footprint: a systematic review. Int. J. Life Cycle Assess. 27, 342–352. https://doi.org/10.1007/s11367-022-02022-3

Pelton, R.E.O., Smith, T.M., 2015. Hotspot Scenario Analysis. J. Ind. Ecol. 19, 427–440. https://doi.org/10.1111/jiec.12191

Pérez-López, P., Rajaonison, A., Zebian, B., Bouallou, C., González-Fernández, C., Greses, S., Gómez-Serrano, C., Acién Fernández, F.G., 2025. Exploiting outcomes of life cycle costing to conduct coherent screening social life cycle assessments of emerging systems: a case study of microalgae biorefineries. Int. J. Life Cycle Assess. 30, 770–791. https://doi.org/10.1007/s11367-024-02427-2

Pizzi, S., Mastroleo, G., Venturelli, A., Caputo, F., 2024. The digitalization of sustainability reporting processes: A conceptual framework. Bus. Strategy Environ. 33, 1040–1050. https://doi.org/10.1002/bse.3544

Pollok, L., Spierling, S., Endres, H.-J., Grote, U., 2021. Social Life Cycle Assessments: A Review on Past Development, Advances and Methodological Challenges. Sustainability 13, 10286. https://doi.org/10.3390/su131810286

Rahman, Arif, Oktaufik, M.A.M., Sasongko, T.W., Guntoro, I., Soedjati, D., Abbas, N., Rahman, Abdul, Ulfah, F., Widiarto, A., Siswanto, Dharmawan, Trihadi, S.E.Y., Kusrestuwardani, Prihatin, A.L., Hadi, A., Indrijarso, S., Rahardjo, P., Barkah, A., Febijanto, I., Sasongko, N.A., 2025. Current scenario and potential of waste cooking oil as a feedstock for biodiesel production in Indonesia: Life cycle sustainability assessment (LCSA) review. Case Stud. Chem. Environ. Eng. 11, 101067. https://doi.org/10.1016/j.cscee.2024.101067

Rambaud, A., Richard, J., 2015. The “Triple Depreciation Line” instead of the “Triple Bottom Line”: Towards a genuine integrated reporting. Crit. Perspect. Account. 33, 92–116. https://doi.org/10.1016/j.cpa.2015.01.012

Ramos Huarachi, D.A., Piekarski, C.M., Puglieri, F.N., de Francisco, A.C., 2020. Past and future of Social Life Cycle Assessment: Historical evolution and research trends. J. Clean. Prod. 264, 121506. https://doi.org/10.1016/j.jclepro.2020.121506

Ratnatunga, J., Tse, M.S.C., Balachandran, K.R., 2012. Cost Management in Sri Lanka: A Case Study on Volume, Activity and Time as Cost Drivers. Int. J. Account. 47, 281–301.

Rebitzer, G., Ekvall, T., Frischknecht, R., Hunkeler, D., Norris, G., Rydberg, T., Schmidt, W.-P., Suh, S., Weidema, B.P., Pennington, D.W., 2004. Life cycle assessment: Part 1: Framework, goal and scope definition, inventory analysis, and applications. Environ. Int. 30, 701–720. https://doi.org/10.1016/j.envint.2003.11.005

Reimers, N., Gurevych, I., 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks, in: Inui, K., Jiang, J., Ng, V., Wan, X. (Eds.), Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). Presented at the EMNLP-IJCNLP 2019, Association for

Computational Linguistics, Hong Kong, China, pp. 3982–3992. https://doi.org/10.18653/v1/D19-1410

Reinales, D., Zambrana-Vasquez, D., Saez-De-Guinoa, A., 2020. Social Life Cycle Assessment of Product Value Chains Under a Circular Economy Approach: A Case Study in the Plastic Packaging Sector. Sustainability 12, 6671. https://doi.org/10.3390/su12166671

Resta, B., Gaiardelli, P., Pinto, R., Dotti, S., 2016. Enhancing environmental management in the textile sector: An Organisational-Life Cycle Assessment approach. J. Clean. Prod. 135, 620–632. https://doi.org/10.1016/j.jclepro.2016.06.135

Retamal, M., Martinez-Fernandez, C., Sharpe, S., ILO Regional Office for Asia and the Pacific., International Labour Organization., 2022. Assessing the impact: environmental impact assessment in the textile and garment sector in Bangladesh, Cambodia, Indonesia and Viet Nam. ILO, Bangkok. https://doi.org/10.54394/YCEP9777

Rimano, M., Simboli, A., Taddeo, R., Del Grosso, M., Raggi, A., 2021. The Environmental Impact of Organizations: A Pilot Test from the Packaging Industry Based on Organizational Life Cycle Assessment. Sustainability 13, 11402. https://doi.org/10.3390/su132011402

Ritchie, H., 2020. Sector by sector: where do global greenhouse gas emissions come from? Our World Data.

Rödger, J.-M., Kjær, L.L., Pagoropoulos, A., 2018. Life Cycle Costing: An Introduction, in: Hauschild, M.Z., Rosenbaum, R.K., Olsen, S.I. (Eds.), Life Cycle Assessment: Theory and Practice. Springer International Publishing, Cham, pp. 373–399. https://doi.org/10.1007/978-3-319-56475-3_15

Rodrigues, C., Rodrigues, E., S. Fernandes, M., Tadeu, S., 2024. Prospective life cycle approach to buildings' adaptation for future climate and decarbonization scenarios. Appl. Energy 372, 123867. https://doi.org/10.1016/j.apenergy.2024.123867

Rodrigues, D., 2024. The Power of Digital Platforms in Life Cycle Assessments. CarbonBright. URL https://carbonbright.co/digital-solutions-for-life-cycle-assessments (accessed 7.25.25).

Roos Lindgreen, E., Vermeulen, W.J.V., 2023. In search for ground rules for product-oriented full cost accounting methods: Ensuring construct validity. Environ. Sustain. Indic. 19, 100275. https://doi.org/10.1016/j.indic.2023.100275

Rossi, S., 2007. The Theory of Money Emissions (Chapters). Edward Elgar Publishing.

Russo Garrido, S., Parent, J., Beaulieu, L., Revéret, J.-P., 2018. A literature review of type I SLCA—making the logic underlying methodological choices explicit. Int. J. Life Cycle Assess. 23, 432–444. https://doi.org/10.1007/s11367-016-1067-z

Saberi, S., Kouhizadeh, M., Sarkis, J., Shen, L., 2019. Blockchain technology and its relationships to sustainable supply chain management. Int. J. Prod. Res. 57, 2117–2135. https://doi.org/10.1080/00207543.2018.1533261

Sairinen, R., Sidorenko, O., Tiainen, H., 2021. A research framework for studying social impacts: Application to the field of mining. Environ. Impact Assess. Rev. 86, 106490. https://doi.org/10.1016/j.eiar.2020.106490

Sala, S., Crenna, E., Secchi, M., Sanyé-Mengual, E., 2020. Environmental sustainability of European production and consumption assessed against planetary boundaries. J. Environ. Manage. 269, 110686. https://doi.org/10.1016/j.jenvman.2020.110686

Sala, S., Vasta, A., Mancini, L., Dewulf, J., Rosenbaum, E., 2015. Social Life Cycle Assessment: State of the art and challenges for supporting product policies [WWW Document]. JRC Publ. Repos. https://doi.org/10.2788/53485

Saldana, J., 2021. The Coding Manual for Qualitative Researchers.

Salemdeeb, R., zu Ermgassen, E.K.H.J., Kim, M.H., Balmford, A., Al-Tabbaa, A., 2017. Environmental and health impacts of using food waste as animal feed: a comparative analysis of food waste management options. J. Clean. Prod., Towards eco-efficient agriculture and food systems: selected papers addressing the global challenges for food systems, including those presented at the Conference "LCA for Feeding the planet and energy for life" (6-8 October 2015, Stresa & Milan Expo, Italy) 140, 871–880. https://doi.org/10.1016/j.jclepro.2016.05.049

Sancha Fernández, C., Wong, C.W.Y., Giménez Thomsen, C., 2016. Buyer-supplier relationships on environmental issues: A contingency perspective. J. Clean. Prod. 112, 1849–1860. https://doi.org/10.1016/j.jclepro.2014.09.026

SASB, 2025. New SASB Standards Navigator now available, Sustainability Accounting Standards Board.

Savall, H., Zardet, V., 2008. Mastering hidden costs and socio-economic performance., IAP Information Age Publishing Inc.

SBTi, 2024a. CATALYZING VALUE CHAIN DECARBONIZATION: Corporate Survey Results.

SBTi, 2024b. ALIGNING CORPORATE VALUE CHAINS TO GLOBAL CLIMATE GOALS. Science Based Targets Initiative.

SBTi, 2023. ENGAGING SUPPLY CHAINS ON THE DECARBONIZATION JOURNEY - A GUIDE TO DEVELOPING AND ACHIEVING SCOPE 3 SUPPLIER ENGAGEMENT TARGETS (Guidance No. V1.0). Science Based Targets Initiative.

Schneider, D., Jordan, P., Dietz, J., Zaeh, M.F., Reinhart, G., 2023. Concept for Automated LCA of Manufacturing Processes. Procedia CIRP, 30th CIRP Life Cycle Engineering Conference 116, 59–64. https://doi.org/10.1016/j.procir.2023.02.011

Schöpper, H., Kersten, W., 2021. Using Natural Language Processing for Supply Chain Mapping: A Systematic Review of Current Approaches, in: ResearchGate.

Schoun, G., Saint-Front, J. de, Saint-Front, P. de, Veillard, M., 2012. Manifeste pour une comptabilité universelle, Un autre regard / Paris School of Business.

Securities and Exchange Commission, 2024. SEC Adopts Rules to Enhance and Standardize Climate-Related Disclosures for Investors.

Seror, P., 2005. Conductions nerveuses: techniques, pièges et solutions. Elsevier, Paris.

SETAC, 2011. Environmental Life Cycle Costing: A Code of Practice.

SETAC, 1993. Guidelines for Life-Cycle Assessment: A 'Code of Practice.' Environ. Sci. Pollut. Res., from the workshop held at Sesimbra, Portugal, Society of Environmental Toxicology and Chemistry (SETAC) 1, 55–55. https://doi.org/10.1007/BF02986927

Seuring, S., Müller, M., 2008. From a literature review to a conceptual framework for sustainable supply chain management. J. Clean. Prod. 16, 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Shaikh, F., 2024. Power BI and Its Role in Promoting Sustainability in Enterprises. Iqra Technol. URL https://iqratechnology.com/blogs/sustainable-bi-power-bis-role-in-promoting-2/ (accessed 7.25.25).

Shan, H., Li, Y., Shi, J., 2020. Influence of Supply Chain Collaborative Innovation on Sustainable Development of Supply Chain: A Study on Chinese Enterprises. Sustainability 12, 2978. https://doi.org/10.3390/su12072978

Sheen, R., 2023. ESG Developments: The Impact of CSRD on Pay Equity. Trusaic. URL https://trusaic.com/blog/esg-developments-the-impact-of-csrd-on-pay-equity/ (accessed 7.27.25).

Shekarian, E., Ijadi, B., Zare, A., Majava, J., 2022. Sustainable Supply Chain Management: A Comprehensive Systematic Review of Industrial Practices. Sustainability 14, 7892. https://doi.org/10.3390/su14137892

Siguenza-guzman, L., Abbeele, A.V.D., Vandewalle, J., Verhaaren, H., Cattrysse, D., 2013. Recent Evolutions in Costing Systems: A Literature Review of Time-Driven Activity-Based Costing. Rev. Bus. Econ. Lit. 58, 34–65.

Simons, R., 1994. How managers use innovative control systems to drive strategic renewal.

Sinha, A., 2025. Green AI: The Rise of Sustainable LLMs. Medium. URL https://medium.com/@akankshasinha247/green-ai-the-rise-of-sustainable-llms-22f5858eeb20 (accessed 7.25.25).

Slaper, T.F., Hall, T.J., 2011. The Triple Bottom Line: What Is It and How Does It Work? Indiana Business Review.

Smaldone, F., Lagger, J., Mainolfi, G., 2025. Profiling employability skills for life cycle professionals amid the circular and digital economy. Int. J. Life Cycle Assess. https://doi.org/10.1007/s11367-025-02490-3

SNBPE, 2024. betie 4.0.

Sonnemann, G., Margni, M. (Eds.), 2015. Life Cycle Management, LCA Compendium – The Complete World of Life Cycle Assessment. Springer Netherlands, Dordrecht. https://doi.org/10.1007/978-94-017-7221-1

Sphera, 2024. LCA Software review of Sphera (Gabi). Your Guide LCA Softw. URL https://lca-software.org/sphera-gabi/ (accessed 7.22.25).

Springer, S.K., Wulf, C., Zapp, P., 2025. PSILCA database for social life cycle assessment: worker hours vs. raw values approach. Int. J. Life Cycle Assess. 30, 1078–1098. https://doi.org/10.1007/s11367-024-02348-0

Srijit, K., Mathiyazhagan, K., Vikas, K., et al., 2021. Assessing the key enablers for Industry 4.0 adoption using MICMAC analysis: A case study. International Journal of Productivity and Performance Management.

Stadler, K., 2021. Pymrio – A Python Based Multi-Regional Input-Output Analysis Toolbox. J. Open Res. Softw. 9. https://doi.org/10.5334/jors.251

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J.H., Theurl, M.C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K.-H., de Koning, A., Tukker, A., 2018. EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. J. Ind. Ecol. 22, 502–515. https://doi.org/10.1111/jiec.12715

Stake, R.E., 1995. The art of case study research, Nachdr. ed. Sage Publ, Thousand Oaks, Calif.

Stenzel, A., Waichman, I., 2023. Supply-chain data sharing for scope 3 emissions. Npj Clim. Action 2, 1–7. https://doi.org/10.1038/s44168-023-00032-x

Stephan, A., Crawford, R.H., Bontinck, P.-A., 2019. A model for streamlining and automating path exchange hybrid life cycle assessment. Int. J. Life Cycle Assess. 24, 237–252. https://doi.org/10.1007/s11367-018-1521-1

Steubing, B., Wernet, G., Reinhard, J., Bauer, C., Moreno-Ruiz, E., 2016. The ecoinvent database version 3 (part II): analyzing LCA results and comparison to version 2. Int. J. Life Cycle Assess. 21, 1269–1281. https://doi.org/10.1007/s11367-016-1109-6

Stridsland, T., Biørnstad, W., Vigen, K., Østergaard, K.L., Sanderson, H., 2023a. No-one left behind: An open access approach to estimating the carbon footprint of a Danish clothing company. J. Clean. Prod. 426, 139126. https://doi.org/10.1016/j.jclepro.2023.139126

Stridsland, T., Stounbjerg, A., Sanderson, H., 2023b. A hybrid approach to a more complete emissions inventory: a case study of Aarhus University. Carbon Manag. 14, 2275579. https://doi.org/10.1080/17583004.2023.2275579

Strømman, A.H., Peters, G.P., Hertwich, E.G., 2009. Approaches to correct for double counting in tiered hybrid life cycle inventories. J. Clean. Prod. 17, 248–254. https://doi.org/10.1016/j.jclepro.2008.05.003

Styles, D., Schoenberger, H., Galvez-Martos, J.-L., 2012. Environmental improvement of product supply chains: Proposed best practice techniques, quantitative indicators and benchmarks of excellence for retailers. J. Environ. Manage. 110, 135–150. https://doi.org/10.1016/j.jenvman.2012.05.021

Suh, S. (Ed.), 2009. Handbook of Input-Output Economics in Industrial Ecology, Eco-Efficiency in Industry and Science. Springer Netherlands, Dordrecht. https://doi.org/10.1007/978-1-4020-5737-3

Suh, S., 2005. Developing a sectoral environmental database for input–output analysis: the comprehensive environmental data archive of the US. Econ. Syst. Res. 17, 449–469. https://doi.org/10.1080/09535310500284326

Suh, S., 2004. Functions, commodities and environmental impacts in an ecological-economic model. Ecol. Econ. 48, 451–467. https://doi.org/10.1016/j.ecolecon.2003.10.013

Suh, S., Huppes, G., 2005. Methods for Life Cycle Inventory of a product. J. Clean. Prod. 13, 687–697. https://doi.org/10.1016/j.jclepro.2003.04.001

Suh, S., Huppes, G., 2000. Gearing input-output model to LCA — part I: General framework for hybrid approach. (No. CML-SSP Working Paper). CML, Leiden University, Leiden, The Netherlands.

Suh, S., Lenzen, M., Treloar, G.J., Hondo, H., Horvath, A., Huppes, G., Jolliet, O., Klann, U., Krewitt, W., Moriguchi, Y., Munksgaard, J., Norris, G., 2004. System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches. Environ. Sci. Technol. 38, 657–664. https://doi.org/10.1021/es0263745

Suzanne Greene, 2023. Freight Transportation | MIT Climate Portal [WWW Document]. URL https://climate.mit.edu/explainers/freight-transportation (accessed 3.19.25).

Tamym, L., Benyoucef, L., Nait Sidi Moh, A., El Ouadghiri, M.D., 2023. Big Data Analytics-based life cycle sustainability assessment for sustainable manufacturing enterprises evaluation. J. Big Data 10, 170. https://doi.org/10.1186/s40537-023-00848-8

Tao, J., Yu, S., 2018. A Meta-model based Approach for LCA-oriented Product Data Management. Procedia CIRP, 25th CIRP Life Cycle Engineering (LCE) Conference, 30 April – 2 May 2018, Copenhagen, Denmark 69, 423–428. https://doi.org/10.1016/j.procir.2017.12.010

TCFD, 2017. Recommendations of the Task Force on Climate-related Financial Disclosures, Task Force on Climate-Related Financial Disclosures.

Teng, Y., Li, C.Z., Shen, G.Q.P., Yang, Q., Peng, Z., 2023. The impact of life cycle assessment database selection on embodied carbon estimation of buildings. Build. Environ. 243, 110648. https://doi.org/10.1016/j.buildenv.2023.110648

TFS, 2024. Scope 3 GHG Emissions Programme. TFS Initiat. URL https://www.tfs-initiative.com/pcf-exchange-solution (accessed 7.22.25).

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. Rev. Int. Econ. 23, 575–605. https://doi.org/10.1111/roie.12178

Toniolo, S., Marson, A., Fedele, A., 2023. Combining organizational and product life cycle perspective to explore the environmental benefits of steel slag recovery practices. Sci. Total Environ. 867, 161440. https://doi.org/10.1016/j.scitotenv.2023.161440

Townsend, J., Barrett, J., 2015. Exploring the applications of carbon footprinting towards sustainability at a UK university: reporting and decision making. J. Clean. Prod. 107, 164–176. https://doi.org/10.1016/j.jclepro.2013.11.004

Tragnone, B.M., Serreli, M., Arzoumanidis, I., Pelino, C.A., Petti, L., 2023. Using the Product Social Impact Life Cycle Assessment (PSILCA) database for product comparison: Confetti case study. Int. J. Life Cycle Assess. 1–23. https://doi.org/10.1007/s11367-023-02173-x

Trébucq, S., 2023. 7. Les outils du contrôle et de la comptabilité au défi de la RSE, in: Le Grand Livre de la RSE. Dunod, pp. 142–160. https://doi.org/10.3917/dunod.trebu.2023.01.0142

Trébucq, S., 2006. Capital humain et comptabilité sociétale : le cas de l'information volontaire des entreprises françaises du SBF120. Comptab. Contrô Audit 12, 103–124. https://doi.org/10.3917/cca.121.0103

Trébucq, S., Valakhanovich, A., 2025. Nouvelles perspectives d'une comptabilité durable conversationnelle : une approche autoethnographique et prospective, in: 46ème Congrès de l'Association Francophone de Comptabilité. Association Francophone de Comptabilité, Saint-Malo, France.

Treloar, G.J., 1997. Extracting Embodied Energy Paths from Input–Output Tables: Towards an Input–Output-based Hybrid Energy Analysis Method. Econ. Syst. Res. 9, 375–391. https://doi.org/10.1080/09535319700000032

Tripathi, Dr.D.R., Sarve, D.I., Khobragade, S.R., 2024. Investigating the Impact of Cloud Computing on Environmental Sustainability. Int. J. Res. Appl. Sci. Eng. Technol. 12, 318–325. https://doi.org/10.22214/ijraset.2024.64515

Trumpp, C., Endrikat, J., Zopf, C., Guenther, E., 2015. Definition, Conceptualization, and Measurement of Corporate Environmental Performance: A Critical Examination of a Multidimensional Construct. J. Bus. Ethics 126, 185–204. https://doi.org/10.1007/s10551-013-1931-8

Tukker, A., de Koning, A., Wood, R., Hawkins, T., Lutter, S., Acosta, J., Rueda Cantuche, J.M., Bouwmeester, M., Oosterhaven, J., Drosdowski, T., Kuenen, J., 2013. Exiopol – Development and Illustrative Analyses of a Detailed Global Mr Ee Sut/Iot. Econ. Syst. Res. 25, 50–70. https://doi.org/10.1080/09535314.2012.761952

Tukker, A., Jansen, B., 2006. Environmental Impacts of Products: A Detailed Review of Studies. J. Ind. Ecol. 10, 159–182.

Turzo, T., Montrone, A., Chirieleison, C., 2024. Social accountability 8000: A quarter century review. J. Clean. Prod. 441, 140960. https://doi.org/10.1016/j.jclepro.2024.140960

Uhlhorn, B., Geißler, G., Jiricka-Pürrer, A., 2024. Exploring the uptake of advanced digital technologies in environmental assessment practice - Experiences from Austria and Germany. J. Environ. Manage. 364, 121412. https://doi.org/10.1016/j.jenvman.2024.121412

UN, 2015a. Paris Agreement. United Nations - Climate Action.

UN, 2015b. THE 17 GOALS | Sustainable Development. URL https://sdgs.un.org/fr/goals (accessed 7.24.25).

UN, 2011. Guiding Principles on Business and Human Rights.

UN, 2004. UNITED NATIONS CONVENTION AGAINST CORRUPTION. UNITED NATIONS OFFICE ON DRUGS AND CRIME.

UNECE, 2011. Gender Statistics Programme of the United Nations Economic Commission for Europe. United Nations Economic Commission for Europe.

UNEP, 2023. Global Guidance for Life Cycle Impact Assessment Indicators and Methods (GLAM) - Life Cycle Initiative. URL https://www.lifecycleinitiative.org/activities/life-cycle-assessment-data-and-methods/global-guidance-for-life-cycle-impact-assessment-indicators-and-methods-glam/ (accessed 7.26.25).

UNEP, 2021. Methodological Sheets for Subcategories in Social Life Cycle Assessment (S-LCA) 2021.

UNEP, 2020. Guidelines for Social Life Cycle Assessment of Products and Organizations. United Nations Environment Programme (UNEP).

UNEP (Ed.), 2015. Guidance on organizational Life Cycle Assessment.

UNEP, 2011. Life Cycle Sustainability Assessment.

UNEPFI, 2024. European Sustainability Reporting Standards (ESRS).

UNFCCC, 2025. ISO 14064 : New International Standards for Greenhouse Gas Quantification, Reporting and Verification.

UNFCCC, 2024. Draft technical paper on AI for climate action (Twenty-nineth meeting No. TEC/2024/29/6), Technology Executive Committee.

Unilever, 2024. Climate Transition Action Plan.

U.S. Bureau of Labor Statistics, 2024. CPI Inflation Calculator.

US EPA, O., 2020. US Environmentally-Extended Input-Output (USEEIO) Models [WWW Document]. URL https://www.epa.gov/land-research/us-environmentally-extended-input-output-useeio-models (accessed 7.22.25).

US EPA, O., 2015. Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) [WWW Document]. URL https://www.epa.gov/chemical-research/tool-reduction-and-assessment-chemicals-and-other-environmental-impacts-traci (accessed 2.24.25).

Valdivia, S., Backes, J.G., Traverso, M., Sonnemann, G., Cucurachi, S., Guinée, J.B., Schaubroeck, T., Finkbeiner, M., Leroy-Parmentier, N., Ugaya, C., Peña, C., Zamagni, A., Inaba, A., Amaral, M., Berger, M., Dvarioniene, J., Vakhitova, T., Benoit-Norris, C., Prox, M., Foolmaun, R., Goedkoop, M., 2021. Principles for the application of life cycle sustainability assessment. Int. J. Life Cycle Assess. 26, 1900–1905. https://doi.org/10.1007/s11367-021-01958-2

Valdivia, S., Sonnemann, G. (Eds.), 2024. Handbook on Life Cycle Sustainability Assessment. Edward Elgar Publishing. https://doi.org/10.4337/9781800378650

Varaniūtė, V., Žičkutė, I., Žandaravičiūtė, A., 2022. The Changing Role of Management Accounting in Product Development: Directions to Digitalization, Sustainability, and Circularity. Sustainability 14, 4740. https://doi.org/10.3390/su14084740

Varma, A., Dixit, N., Ray, S., Kaur, J., 2024. Blockchain technology for sustainable supply chains: A comprehensive review and future prospects. World J. Adv. Res. Rev. 21, 980–994. https://doi.org/10.30574/wjarr.2024.21.3.0804

Veganzones, D., Séverin, E., 2025. Earnings management visualization and prediction using machine learning methods. Int. J. Account. Inf. Syst. 56, 100743. https://doi.org/10.1016/j.accinf.2025.100743

Vieira, L.C., Longo, M., Mura, M., 2024. Impact pathways: the hidden challenges of Scope 3 emissions measurement and management. Int. J. Oper. Prod. Manag. 44, 326–334. https://doi.org/10.1108/IJOPM-01-2024-0049

Vladucu, M.-V., Wu, H., Medina, J., Salehin, K.M., Dong, Z., Rojas-Cessa, R., 2024. Blockchain on Sustainable Environmental Measures: A Review. Blockchains 2, 334–365. https://doi.org/10.3390/blockchains2030016

von Braun, J., Hendriks, S.L., 2023. Full-cost accounting and redefining the cost of food: Implications for agricultural economics research. Agric. Econ. 54, 451–454. https://doi.org/10.1111/agec.12774

Vörösmarty, G., Dobos, I., 2020. A literature review of sustainable supplier evaluation with Data Envelopment Analysis. J. Clean. Prod. 264, 121672. https://doi.org/10.1016/j.jclepro.2020.121672

Wafa, W., Sharaai, A.H., Matthew, N.K., Ho, S.A.J., Akhundzada, N.A., 2022. Organizational Life Cycle Sustainability Assessment (OLCSA) for a Higher Education Institution as an Organization: A Systematic Review and Bibliometric Analysis. Sustainability 14, 2616. https://doi.org/10.3390/su14052616

Waldekker, B., Molnar, S., 2014. Social LCA at SP - Challenges and opportunities.

Walmart, 2024. ESG Reporting - Environmental - Climate Change.

Wang, Y., Han, J.H., Beynon-Davies, P., 2019. Understanding blockchain technology for future supply chains: a systematic literature review and research agenda. Supply Chain Manag. Int. J. 24, 62–84. https://doi.org/10.1108/SCM-03-2018-0148

Watershed, 2024. Watershed CEDA Methodology 2024.

WBCSD, 2023a. Partnership for Carbon Transparency releases updated technical specifications for standardized exchange of emissions data |.

WBCSD, 2023b. Pathfinder Framework Version 2.0. URL (accessed 7.22.25).

Webb, C., Anguilano, L., Troisi, G., Schmidt Rivera, X., 2025. Environmental and economic life cycle sustainability assessment of reusable versus single-use anaesthetic face masks. Environ. Impact Assess. Rev. 114, 107847. https://doi.org/10.1016/j.eiar.2025.107847

Weidema, B.P., 2022. Comparison of the requirements of the GHG Protocol Product Life Cycle standard and the ISO 14040 series.

Weidema, B.P., Wesnæs, M.S., 1996. Data quality management for life cycle inventories—an example of using data quality indicators. J. Clean. Prod. 4, 167–174. https://doi.org/10.1016/s0959-6526(96)00043-1

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology. Int. J. Life Cycle Assess. 21, 1218–1230. https://doi.org/10.1007/s11367-016-1087-8

Wiedmann, T., 2009. A review of recent multi-region input–output models used for consumption-based emission and resource accounting. Ecol. Econ., Special Section: Analyzing the global human appropriation of net primary production - processes, trajectories, implications 69, 211–222. https://doi.org/10.1016/j.ecolecon.2009.08.026

Wiedmann, T.O., Lenzen, M., Barrett, J.R., 2009. Companies on the Scale, Comparing and Benchmarking the Sustainability Performance of Businesses. J. Ind. Ecol. 13, 361–383. https://doi.org/10.1111/j.1530-9290.2009.00125.x

Wiedmann, T.O., Suh, S., Feng, K., Lenzen, M., Acquaye, A., Scott, K., Barrett, J.R., 2011. Application of Hybrid Life Cycle Approaches to Emerging Energy Technologies – The Case of Wind Power in the UK. Environ. Sci. Technol. 45, 5900–5907. https://doi.org/10.1021/es2007287

Wiener, N., 1948. Cybernetics: Or Control and Communication in the Animal and the Machine.

Wohlschlager, D., Bluhm, H., Beucker, S., Pohl, J., Fröhling, M., 2023. Overcoming challenges in life cycle assessment of smart energy systems – A map of solution approaches. J. Clean. Prod. 423, 138584. https://doi.org/10.1016/j.jclepro.2023.138584

WRI, WBCSD, 2013. Technical Guidance for Calculation Scope 3 Emissions (Version 1.0). World Resources Institute & World Business Council for Sustainable Development.

WRI, WBCSD, 2011a. Corporate Value Chain (Scope 3) Accounting and Reporting Standard. World Resources Institute & World Business Council for Sustainable Development.

WRI, WBCSD, 2011b. Product Standard | GHG Protocol.

Yang, C.-H., Lee, K.-C., Chen, H.-C., 2016. Incorporating carbon footprint with activity-based costing constraints into sustainable public transport infrastructure project decisions. J. Clean. Prod. 133, 1154–1166. https://doi.org/10.1016/j.jclepro.2016.06.014

Yang, Y., Ingwersen, W.W., Hawkins, T.R., Srocka, M., Meyer, D.E., 2017. USEEIO: A new and transparent United States environmentally-extended input-output model. J. Clean. Prod. 158, 308–318. https://doi.org/10.1016/j.jclepro.2017.04.150

Yang, Y., Park, Y., Smith, T.M., Kim, T., Park, H.-S., 2022. High-Resolution Environmentally Extended Input–Output Model to Assess the Greenhouse Gas Impact of Electronics in South Korea. Environ. Sci. Technol. 56, 2107–2114. https://doi.org/10.1021/acs.est.1c05451

Yin, R.K., 2014. Case study research: design and methods, Fifth edition. ed. SAGE, Los Angeles.

Yıldız-Geyhan, E., Altun-Çiftçioğlu, G.A., Kadırgan, M.A.N., 2017. Social life cycle assessment of different packaging waste collection system. Resour. Conserv. Recycl. 124, 1–12. https://doi.org/10.1016/j.resconrec.2017.04.003

Yıldız-Geyhan, E., Yılan, G., Altun-Çiftçioğlu, G.A., Kadırgan, M.A.N., 2019. Environmental and social life cycle sustainability assessment of different packaging waste collection systems. Resour. Conserv. Recycl. 143, 119–132. https://doi.org/10.1016/j.resconrec.2018.12.028

Yu, M., Robati, M., Oldfield, P., Wiedmann, T., Crawford, R., Nezhad, A.A., Carmichael, D., 2020. The impact of value engineering on embodied greenhouse gas emissions in the built environment: A hybrid life cycle assessment. Build. Environ. 168, 106452. https://doi.org/10.1016/j.buildenv.2019.106452

Yu, M., Wiedmann, T., 2018. Implementing hybrid LCA routines in an input–output virtual laboratory. J. Econ. Struct. 7, 33. https://doi.org/10.1186/s40008-018-0131-1

Zafrilla, J.E., Cadarso, M.-Á., Monsalve, F., De La Rúa, C., 2014. How Carbon-Friendly Is Nuclear Energy? A Hybrid MRIO-LCA Model of a Spanish Facility. Environ. Sci. Technol. 48, 14103–14111. https://doi.org/10.1021/es503352s

Zappatore, M., Ruggieri, G., 2024. Adopting machine translation in the healthcare sector: A methodological multi-criteria review. Comput. Speech Lang. 84, 101582. https://doi.org/10.1016/j.csl.2023.101582

Zheng, S., Wen, J., 2024. Green public procurement and corporate environmental performance: An empirical analysis based on data from green procurement contracts. Int. Rev. Econ. Finance 96, 103578. https://doi.org/10.1016/j.iref.2024.103578

Zhong, X., Hu, M., Deetman, S., Steubing, B., Lin, H.X., Hernandez, G.A., Harpprecht, C., Zhang, C., Tukker, A., Behrens, P., 2021. Global greenhouse gas emissions from residential and commercial building materials and mitigation strategies to 2060. Nat. Commun. 12, 6126. https://doi.org/10.1038/s41467-021-26212-z

Zhong, Y., Chen, X., Wang, Z., Lin, R.F.-Y., 2024. The nexus among artificial intelligence, supply chain and energy sustainability: A time-varying analysis. Energy Econ. 132, 107479. https://doi.org/10.1016/j.eneco.2024.107479