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Application of Artificial Intelligence to the Resilience or Viability of Supply Chains in the Context of a Health Crisis

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« The only true wisdom is in knowing

you know nothing »

Socrates

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Chapter 1

General Introduction

1.1 Context and motivation

In the face of growing global uncertainties, supply chain (SC) disruptions have become increasingly frequent and impactful. Factors such as pandemics, natural disasters, political instability, and infrastructure fragility can severely compromise the continuity of supply operations. This is particularly critical in the pharmaceutical sector, where delays or shortages can endanger public health and human lives. Pharmaceutical Supply Chains (PSCs) are inherently complex due to strict regulatory requirements, cold chain constraints, heterogeneous stakeholders, and the vital importance of timely delivery of medicines and vaccines.

The COVID-19 pandemic brought these challenges to the forefront, exposing the fragility of PSCs at both global and local levels. In parallel, localized health crises such as the 2015–2016 outbreaks of Zika (ZIKV) and Chikungunya (CHIKV) in French Guiana (FG) further highlighted the systemic vulnerabilities of healthcare supply chains in remote and underserved regions. FG, as an overseas territory of France situated in the Amazonian region, faces unique logistical and operational constraints—including geographic isolation, dependency on air and maritime transportation, limited storage infrastructure, and disparities in healthcare access. During these outbreaks, the regional health system struggled with erratic demand surges, stockouts, and fragmented coordination across the supply chain network, especially in reaching decentralized health centers (CDPS).

The urgency to build PSCs that are not only resilient to disruptions but also viable in the long term has stimulated the exploration of digital and intelligent solutions. Recent advances in Artificial Intelligence (AI), the Internet of Things (IoT), blockchain, and digital twin technologies offer new capabilities to improve forecasting, visibility, traceability, and decision-making in complex supply networks. AI-based models—particularly interpretable and hybrid approaches—can support scenario analysis, risk identification, and resource allocation under uncertainty. Digital twins, by enabling virtual replicas of supply systems, allow real-time monitoring and simulation of various disruption-response strategies.

However, the adoption of these technologies in PSCs, especially in resource-constrained or crisis-prone settings, remains limited. Most existing literature addresses these innovations in industrial or stable environments, with a predominant focus on theoretical modeling rather than empirical validation in the field. There is a critical need to bridge this gap by grounding research in real-world data and operational realities, particularly in fragile health ecosystems.

This dissertation is positioned at the intersection of supply chain resilience, AI technologies,

and public health crisis management. It aims to explore how digital and intelligent tools can enhance the resilience and long-term viability of PSCs in the context of complex and high-stakes disruptions.

It particularly draws on two case studies: (1) the supply of COVID-19 vaccines in France, (2) the pharmaceutical supply response during the Zika and Chikungunya epidemics in FG, and a simulation-based analysis of PSC resilience strategies in health emergencies. By integrating data science, modeling, and practical insights, this research contributes to both theory and practice in resilient and digitally enabled healthcare logistics.

1.2 Objectives and Research Questions

The overall objective of this research is to investigate how AI-based technologies and digital tools can be leveraged to strengthen the resilience and viability of pharmaceutical supply chains, particularly in contexts affected by public health crises and systemic vulnerabilities.

Each chapter is designed to contribute unique insights to the overarching theme of AI adoption in enhancing supply chain resilience and viability.

Chapter 2: **The Application of Artificial Intelligence Technologies in the Resilience and the Viability of Supply Chains: A Systematic Literature Review**

The objective of this chapter is to systematically explore and synthesize existing academic literature on the application of Artificial Intelligence (AI) technologies in enhancing supply chain resilience (SCR) and supply chain viability (SCV). Considering the increasing frequency and severity of global disruptions—such as pandemics, geopolitical conflicts, economic volatility, and climate-related crises, this chapter aims to understand how AI contributes to mitigating risks, enabling adaptive strategies, and ensuring the continuity and sustainability of supply chains. By employing a structured review protocol (TCCM), this chapter provides a comprehensive understanding of the theoretical foundations, contextual applications, methodological approaches, and key constructs discussed in the existing body of knowledge. Ultimately, it seeks to identify research gaps and propose directions for future investigations to advance the role of AI in resilient and viable supply chain systems.

Research Questions:

- **RQ1:** What does current research show about AI for supply chain resilience and viability, including the main theories, contexts, and methods used?
- **RQ2:** Which variables and outcomes are most studied, and how does AI improve performance under disruption?

Chapter 3: **The Viability of Supply Chains with Interpretable Learning Systems: The Case of COVID-19 Vaccine Deliveries**

The objective of this chapter is to investigate the role of interpretable learning systems, specifically artificial intelligence (AI) technologies, in enhancing the resilience and viability of supply chains during pandemic crises. The COVID-19 pandemic revealed major vulnerabilities in global supply networks, particularly in the healthcare sector, where timely delivery and equitable distribution of vaccines were critical. This chapter aims to analyze how interpretable AI systems, such as artificial neural networks, can support decision-making processes, improve risk visibility, and enable better forecasting and planning in the context of emergency supply chain operations. A descriptive case study focused on COVID-19 vaccine deliveries in France is used to ground the analysis in a real-world context and assess the practical impact of AI-driven approaches on supply chain performance.

Research Questions:

- **RQ3:** How can interpretable AI systems strengthen supply chain resilience and long-term viability during pandemic crises?
- **RQ4:** What strategic and operational benefits arise from using interpretable AI for forecasting vaccine deliveries and vaccination rates, given factors like demographics, storage sites, suppliers, and transport modes?

Chapter 4: **Modeling Pharmaceutical Supply Chain Resilience During Arboviral Epidemics: Evidence from Chikungunya and Zika in French Guiana**

The objective of this chapter is to investigate the vulnerabilities and resilience of the pharmaceutical supply chain (PSC) in French Guiana during the 2015–2016 Zika and Chikungunya outbreaks. By employing a hybrid research methodology that integrates empirical data with simulation-based analysis through a digital twin model, the chapter aims to assess the performance of the PSC under epidemic-induced stress and to develop targeted strategies to enhance its resilience, responsiveness, and viability in anticipation of future public health crises.

Research Questions:

- **RQ5:** How did the ZIKV and CHIKV outbreaks affect the performance of the PSC in FG?
- **RQ6:** What measures can be implemented to enhance the resilience of the PSC in anticipation of future health crises?

By addressing these research questions, this thesis aims to contribute to academic understanding and provide practical recommendations for optimizing AI adoption in the aeronautics sector.

1.3 Organization of the Manuscript

The organization of this thesis is presented in **Figure 1.1**. Following the general introduction in Chapter 1, which provides the context, motivation, objectives, and research questions, the subsequent chapters address the research questions.

Chapter 2 provides a systematic literature review on the role of Artificial Intelligence (AI) in enhancing supply chain (SC) resilience and viability. In the face of increasing disruptions, ranging from natural disasters to geopolitical crises, resilience and viability have become critical, especially within the Industry 5.0 and sustainability context. Despite the rise of digital technologies, the specific contribution of AI remains underexplored in existing research. Using the TCCM (Theory, Context, Characteristics, Methodology) framework, the chapter analyzes high-ranking scientific articles to identify key theories, types of crises, industries, and methods studied. Key findings highlight a focus on economic, healthcare, and environmental risks, with frequent use of theories like dynamic capabilities, fuzzy set theory, and OIPT. While manufacturing, electronics, and food industries dominate, variables studied span sectors such as logistics, health, environment, and finance. The review also reveals significant research gaps and suggests future directions, offering valuable insights for advancing both academic research and practical applications of AI in resilient and sustainable SCs.

Chapter 3 investigates the role of interpretable learning systems, particularly AI technologies, in strengthening supply chain viability and resilience. Using the scenario case of COVID-19 vaccine deliveries in France, the study adopts a descriptive and empirical approach to explore how these systems support decision-making during crises. The findings demonstrate the effectiveness of interpretable AI in predicting deliveries and vaccination rates, optimizing SC's operations, guiding prioritization strategies, and enhancing resource utilization.

Chapter 4 examines the vulnerabilities of pharmaceutical supply chains (PSC) during arboviral

epidemics, using the 2015–2016 Zika and Chikungunya outbreaks in French Guiana as a case study. Through a simulation-based approach with anylogistix software, the research develops a digital twin of the supply chain to analyze its performance under epidemic stress. Combining empirical data and structured assumptions, the study identifies critical bottlenecks in product availability, logistics coordination, and stock management. It proposes targeted strategies to strengthen resilience focusing on anticipation, responsiveness, and robustness. While based on a complex real-world scenario, the methodology and resilience framework are adaptable to other, less intricate contexts. This work offers practical, scalable tools for improving pharmaceutical logistics during health crises and contributes to global preparedness by providing actionable insights for policymakers, healthcare professionals, and SC's stakeholders.

Finally, Chapter 5 concludes the thesis by synthesizing the main findings from the preceding chapters, highlighting the theoretical and practical contributions of the research to the fields of supply chain management, artificial intelligence, and health logistics. It also highlights the limitations of the current work and outlines promising avenues for future research, with a particular emphasis on advancing methodological approaches, expanding empirical validation across diverse contexts, and examining the long-term impact of digital technologies on supply chain resilience and viability.

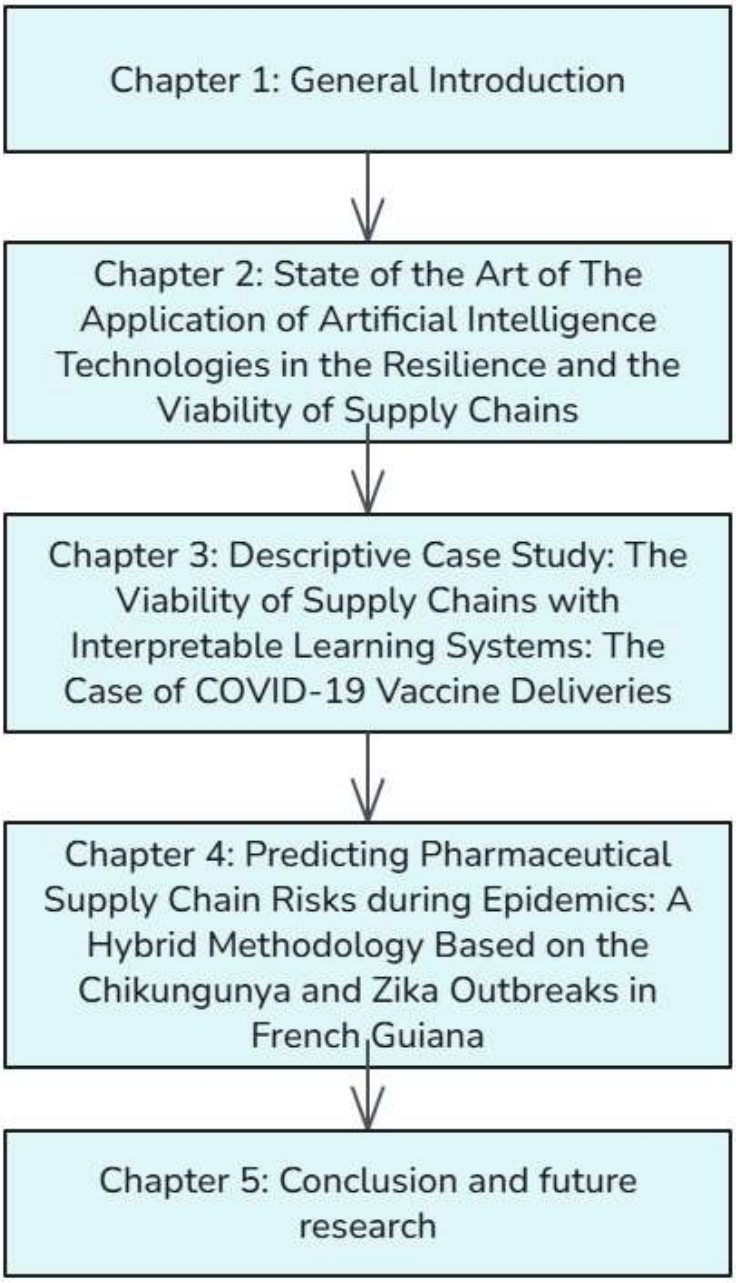


Figure 1.1: General diagram of the organization of the manuscript

1.4 Publications

This section highlights the scientific articles that have been published or are currently under review, representing a significant portion of the outcomes derived from this thesis.

- S.Zaoui et al , ***The Viability of Supply Chains with Interpretable Learning Systems: The Case of COVID-19 Vaccine Deliveries****, Global Journal of Flexible Systems Management, https://doi.org/10.1007/s40171-023-00357-w (Published)*
- (Chou *et al.*, 2024)*,* ***Hualien City, Taiwan Earthquake ,PRJ-4613 | steer- 2024*** https://doi.org/10.17603/ds2-0d2z-9682 *(Published)*
- S.Zaoui et al, ***Sustainability: the main pillar of Industry 5.0*****,** October 2024, DOI: https://doi.org/10.55432/978-1-6692-0007-9_13, Oklahoma International Publishing, USA 2024 okip Academia & Industry *(Published)*
- *S.Zaoui et al,* ***The Application of Artificial Intelligence Technologies in the Resilience and the Viability of Supply Chains: A Systematic Literature Review,*** Accepted in *Journal of Production Planning and Control,*https://doi.org/10.1080/09537287.2025.2563616 *(Published)*
- *S.Zaoui et al,* ***Modeling Pharmaceutical Supply Chain Resilience During Arboviral Epidemics: Evidence from Chikungunya and Zika in French Guiana*** **-** Submission in International Journal of Production Research.

Chapter 2

The Application of Artificial Intelligence Technologies in the Resilience and the Viability of Supply Chains: A Systematic Literature Review

ABSTRACT

The viability and resilience of supply chains (SC) are crucial today given the increasing frequency of sudden disruptions, such as natural/environmental disasters, sanitary/healthcare crises, economic or political instabilities, cyber-attacks, and wars, that regularly impede their smooth operation. Nowadays, resilience and viability issues are also closely tied to sustainability issues and the development of advanced technologies in the industry 5.0 context. Simultaneously, although the emergence of digital technologies provides an expanding array of means to address viability and resilience issues in SC, the specific role played by a major technology like artificial intelligence (AI) remains barely assessed in the literature. Thus, this chapter presents a global and comprehensive exploration of AI technology's role in enhancing SC's resilience and viability. A systematic literature review is carried out through a rigorous selection of articles published in highly-ranked scientific journals. The analysis is performed through a structured theory, context, characteristics, and methodology (*TCCM) protocol allowing the identification of the most prominent theories, contexts (industries, locations, type of crisis), characteristics (antecedents, outcomes, and key variables), and methodologies (types of research and methods). The findings indicate that a broad range of theories and types of risks are addressed, with a predominance of studies focusing on economic, healthcare, and environmental risks. Additionally, the most prominent theories include the dynamic capabilities theory, fuzzy set theory, and organizational information processing theory (OIPT). Although three industries are more often studied (the manufacturing, electronic, and food industries), the key variables commonly investigated (mostly through quantitative methods) are drawn from various sectors, including logistics, environment, economy, health, technology, and finance. More generally, the findings also allow us to identify the current main research gaps and to propose several future research avenues. This configuration not only enriches the comprehension of the dynamics at play but also serves as an invaluable asset for practitioners and researchers alike, navigating the optimization of adaptability and sustainability within SC. It marks a substantial contribution to the ongoing discourse on the transformative influence of AI in fortifying the global dynamics of SC.*

Keywords: *Supply chain, resilience, viability, risk prediction, machine learning, artificial intelligence, sustainability*

2.1 Introduction

Risks in the supply chain (SC) can result from many factors, such as political or economic conflicts or natural disasters. Not surprisingly, the SC is not unrelated to the social, political, and economic context that surrounds it (Santhi et al., 2022). For instance, with inflation taking hold worldwide, commodity prices are soaring, and input costs and freight rates have surged since the summer of 2020. The prices of many commodities have broken records, and this has been particularly the case for energy, especially with soaring prices for gas, hydrocarbons, metals, timber, and food. The widespread rise in raw materials and commodities prices has also led to higher consumer prices. Faced with this situation, we are witnessing an economic recession and the loss of many SC assets. In addition, geopolitical risk, which had taken a back seat during the pandemic, is now a prominent issue that needs to be addressed (Ozdemir et al., 2022). Companies must examine their SCs, assess the risk exposure, and build contingency plans to improve their associated viability and resilience (Dubey, 2023).

SC resilience can be defined as the ability of a SC to detect, adapt, and react to disturbances to restore its original structure and functions (Ponomarov et al., 2009). In addition, SC viability can be defined as the ability of a SC to maintain itself and survive in a changing environment through a redesign of structures and replanning of performance with long-term impacts (Ivanov 2020). SCs need to become more resilient if they want to provide an adequate service level and survive through disruptive events (Hosseini et al., 2019). Resilience and viability issues are also closely tied to sustainability issues and the development of advanced technologies in the current era of Industry 5.0 (Ahmed et al., 2023).

Nowadays, as businesses navigate through increasingly complex globalized networks, with volatile markets requiring agility for survival, leveraging digital technologies as tools for controlling risk factors is becoming imperative (Meyer et al., 2023).

Organizations recognize that disrupting these integrated networks can have far-reaching consequences; hence, substantial investments are necessary to introduce new technologies from industry leaders and recruitment strategies to hire top-talent individuals who specialize in monitoring evolving global conditions (Belhadi et al., 2022). In this context, agility, lean, and flexibility are crucial in enhancing supply chain resilience (SCR) and supply chain viability (SCV) (Aprile* et al., 2005). Agility facilitates quick adjustments to unexpected challenges, lean principles enhance efficiency by reducing waste while preserving responsiveness, and flexibility guarantees that SCs can dynamically adjust operations in reaction to shifting market

demands (Al Doghan et al., 2023; Manzoor et al., 2022; Reyes et al., 2023).

There is a growing interest in the literature on the role of various digital technologies (e.g., blockchain, the Internet of Things, big data analytics, digital twins) in mitigating the effects of disruptions on SCs. For example, artificial intelligence-powered demand forecasting models have been instrumental in SCR and SCV, particularly during the COVID-19 pandemic, where they enabled businesses to anticipate supply shortages, optimize inventory levels, and adjust procurement strategies in response to fluctuating market conditions (Ivanov et al., 2021).

While these technologies contribute to SCV and SCR, artificial intelligence (AI) plays a particularly transformative role by enabling predictive analytics, real-time monitoring, and automated decision-making to proactively manage risks and disruptions. However, despite the central role played by AI in enhancing SCV and SCR (Queiroz et al., 2022), there remains a noticeable gap in the literature. Only a limited number of studies specifically focus on AI's contributions (Modgil et al., 2022; Riahi et al., 2021) and those that do primarily examine specific industries, such as the food sector (Yakoubi et al., 2023) or manufacturing (R. Sharma *et al.*, 2022). More broadly, none of these studies comprehensively address AI's role in reinforcing resilience and viability across diverse industries, various risk types, and the multiple variables that influence SCs. This highlights the need for a more holistic exploration of AI-driven approaches to SCV and SCR.

We address this research gap in this chapter by providing a systematic literature review focusing on the application of AI technologies for the SCR and SCV, with no restrictions either on the type of studied risks or the type of industry.

AI can be defined as the capability of machines to communicate with and imitate the capabilities of humans (Wamba-Taguimdje et al., 2020), and is a promising technology for SC optimization. Integrating AI technologies in SCs leads to problem-solving with higher accuracy, the anticipation of the impacts of external events (Caridi et al., 2004), and it promises real-time monitoring and accurate risk management (Hofmann et al., 2017). Effective employment of innovative techniques such as predictive data analytics and machine learning-assisted decision-making supported by AI tools usually results in optimal efficiency, aiding trouble-spot detection before it balloons into bigger problems, thereby enhancing overall system resiliency (Deiva et al., 2022). AI can also accelerate the decision-making process of top management to increase resilience during disruptions and it can help predict zero error in demand-planning with machine learning (Tian et al., 2024). To deal with the many challenges companies face with global SCs, it is essential to use technologies that provide accurate forecasts and enable

proactive measures before potential problems arise (Romero-Silva et al., 2021; Faruquee et al., 2024). The key challenge for many industries is to make AI an asset that effectively transforms the SC (Jauhar et al., 2023). The fusion of innovative technologies, new IT architectures, big data, and analytics can enhance the end-to-end SCs that meet the needs of relevant stakeholders (Bechtsis et al., 2022).

However, to deal with a greater volume of data and information, AI technologies are necessary to improve situation awareness by enhancing the perception of relevant information, understanding its meaning, and predicting future events (Song et al., 2024).

In addition, the benefits of traceability and its direct impact on SCR are crucial, as they enhance risk awareness and support the overall adaptability and performance of SCs (Razak et al., 2023).

The SC plays a crucial role in the quality of the customer experience, cost control, and the company's agility in the face of market opportunities (Chien et al., 2023). An AI technology can, for instance, predict the level of demand for each product at each store location, balance multiple and competing key performance indicators (Frolov et al., 2021), and significantly minimize shelf discrepancies.

This chapter seeks to identify AI technologies and systems capable of continuously acquiring and analyzing a large volume of data streams to monitor an SC and detect, as quickly as possible, potential risks to speed up its reaction and make it more resilient and viable. Thus, our research question can be expressed as follows: What is the state of the literature on the use of AI technologies for the SCR and SCV?

To answer this question, a systematic literature review has been conducted to examine the current research contributions or directions related to AI and SCR or SCV. The analysis has been performed on relevant related articles from acknowledged scientific journals.

To efficiently structure our analysis by addressing both theoretical and practical dimensions, we rely on the theory, context, characteristics, and methodology (TCCM) protocol (Paul et al., 2019) to evaluate (i) the most used theories in the literature, (ii) the most studied applicative contexts (industries, geographical regions, or types of crises), (iii) the most important characteristics of the studied methods and the key variables, and (iv) the research methodologies employed. Beyond the outlined landscape, we also identify the main research gaps and propose avenues for future research. Our utilization of the TCCM framework guarantees a transparent and reproducible approach, further enhancing the credibility of our investigation.

The chapter's structure includes a background with a summary of related studies in section 2. Next, an elaboration of the methodology used in the systematic review in Section 3. Section 4 presents the most important findings and discussions that address the sub-research questions. Based on these results, Section 5 provides implications for research and practice, as well as future research directions. Finally, Section 6 concludes the chapter.

2.2 Background

Many studies have investigated how AI can improve SCR and SCV. This background section provides an overview of literature reviews already conducted in this area. For each study, we clarify the type of risk addressed, the relevant industry, the technologies analyzed, the specific concepts of resilience or viability discussed, and the review methods utilized. While we recognize the extensive prior work, our goal here is not to duplicate the existing comprehensive discussions but to contextualize our study within the existing literature. Therefore, we emphasize the unique value of our contribution and outline how our review differs from previous work in scope and methodology (Table 1.1). We can notice that none of these studies comprehensively address AI's role in reinforcing both resilience and viability across diverse industries, various risk types, and the multiple variables that influence SCs. This highlights the need for a more holistic exploration of AI-driven approaches to SCV and SCR, that is addressed in this chapter.

Table 2.1: Overview of existing reviews on the application of digital technologies in the management of SC disruptions

Paper	Type of risk in the scope of the study	Industry in the scope of the study	Technologies in the scope of study	Resilience or viability concepts in the scope of the study	Type of Review
(Kassa et al., 2023)	Holistic	Not mentioned	AI	Yes	Systematic literature review between 2010 and 2022
(Zamani et al., 2023)	Holistic	Not mentioned	AI Big data	Yes	Systematic literature review
(Chauhan, Akram and Chauhan, 2023)	Holistic	Not mentioned	Big data analytics Blockchain	Yes	Systematic literature review
(Marinagi et al., 2023)	Holistic	Not mentioned	Industry 4.0	Yes	Systematic literature review
(Beta, Nagaraj and Weerasinghe, 2025)	Health	Not mentionned	AI	Yes	Systematic literature review
(Vishwakarma *et al.*, 2024)	Holistic .	Not mentionned	AI	Yes	Systematic literature review
(Smyth *et al.*, 2024)	Holistic	Not mentionned	AI Prescriptive analytics	Yes	Systematic literature review
(Raja Santhi et al., 2022b)	Economic Health Environmental Financial	Not mentioned	Industry 4.0	Yes	Systematic literature review
(Amentae et al., 2021)	Technological	Food	Blockchain	Yes	Integrative literature review
(Yakoubi et al., 2023)	Holistic	Food delivery systems industry	AI	No	Comprehensive literature review
(Rejeb et al., 2021)	Economic Health Environmental Financial	Food	Blockchain Big data Social media, and geographic information systems.	No	Bibliometric review
(Svoboda et al., 2021)	Health risk COVID-19	Not mentioned	Not mentioned	Yes	Systematic literature review
(Mustapha et al., 2022)	Health risk: COVID-19	Not mentioned	Not mentioned	Yes	Systematic literature review
(Moosavi et al., 2022)	Health risk: COVID-19	Not mentioned	AI Internet of Things (iot) Blockchain	Yes	Systematic literature review with bibliometric analysis
(Riahi et al., 2021)	Economic Technological Health risk Environmental	Manufacturing Electronic Food	AI	No	Systematic literature review combined with a bibliometric

	Financial				analysis
(Tordecilla et al., 2021)	Natural or human-induced disasters, strikes, etc.)	Not mentioned	Not mentioned	Yes	Systematic literature review
	Operational risks (uncertainty in demand, lead time, or other business-related variables)				
(Golan et al., 2021)	Holistic	Pharmaceutical	AI	No	Systematic literature review
			Stress tests		
			Digital twins		
(Sharma et al., 2022)	Economic	Manufacturing industry	AI	Yes	Bibliometric review
	Health				
	Environmental				
	Financial				
(Yang et al., 2022)	Holistic	Not mentioned	Not mentioned	No	Systematic literature review
(Modgil et al., 2022)	Health risk: COVID-19	Not mentioned	AI	No	Systematic literature review
(Hosseini et al., 2019)	Holistic	Not mentioned	Not mentioned	Yes	Systematic literature review
OUR REVIEW	Economic	Manufacturing	AI	Yes	Systematic literature review using the TCCM Framework
	Health risk	Electronic			
	Environmental	Food			
	Financial	IT			
	Technological	Pharmaceutical & Healthcare			
		Automotive			
		Energy			
		Maritime			
		Construction			
		Digital			
		Services			

2.3 Methodology of the research

A systematic literature review methodology was used in this chapter to gain comprehensive insights concerning previously conducted studies on SCR and SCV, using AI technologies (Paul et al., 2020).

A literature review lays the foundation for any research. It helps deliver valuable insights into main research streams, emerging fields, and new knowledge guiding future research initiatives (Fahimnia et al., 2015). It differs from traditional narrative reviews by adopting a replicable, scientific, and transparent producer. It helps to collect all related publications and documents that fit pre-defined inclusion criteria to answer a specific research question (Mengist et al., 2020).

A systematic review collates all the empirical evidence that fits pre-specified eligibility criteria to answer a specific research question. It uses explicit, systematic methods that are selected to

minimize bias, thus providing more reliable findings from which conclusions can be drawn and decisions made.

In the case of this chapter, our goal was to emphasize the triggers, the dimensions, and the concepts related to the application of AI technologies to ensure the SCV by exploring the extant literature and consolidating the findings in the form of interpretable models.

A systematic literature review methodology usually involves two major steps: a rigorous selection of relevant documents and an in-depth analysis of such documents.

2.3.1 Selection of relevant documents

The process used for the selection of relevant documents in our case is presented in Figure 2.1, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) formalism. Three main phases are performed: the identification of documents, screening of documents, and inclusion of documents.

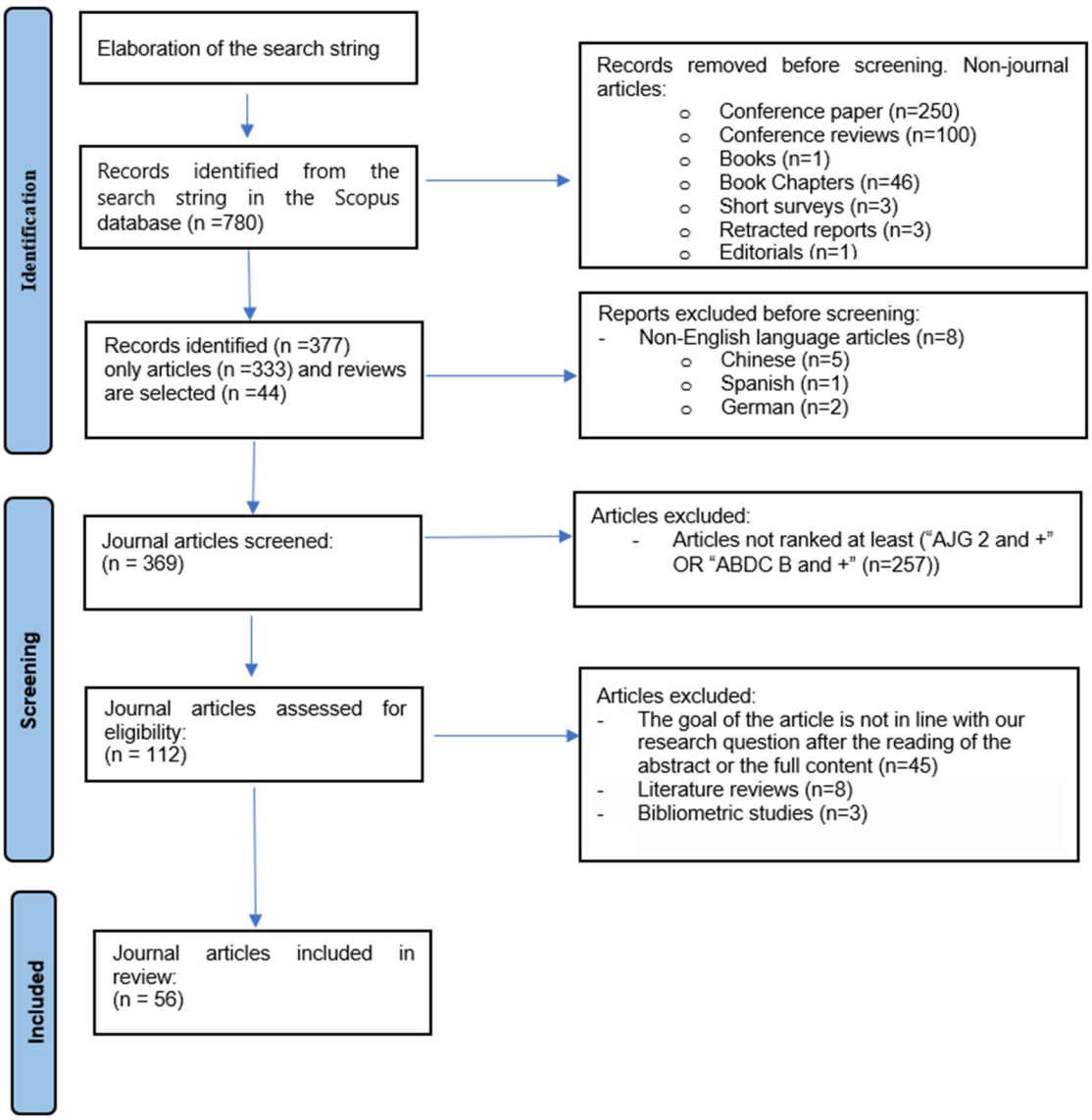


Figure 2.1: PRISMA flow diagram for the systematic review

- **Identification of documents**

For the identification phase, we selected the search engine and the search strings to locate the relevant studies. Bearing in mind that we required a database that provided broad access to a multitude of relevant literature over a specific period, we opted for Scopus, which is among the largest curated abstract and citation databases, with a wide global and regional coverage of scientific journals, conference proceedings, and books (Baas et al., 2020).

One of the main advantages of Scopus is that its coverage is nearly 60% larger than the Web of Science abstract and citation database (Comerio et al., 2018). Furthermore, as described below in the article screening section, we relied exclusively on high-quality articles published in journals listed in widely recognized rankings and indexed in Scopus.

First, we collected the data inputs from the Scopus database by utilizing a combination of

keywords specifically chosen to reference the fields of AI, resilience, viability, and SCs. To thoroughly cover our topic, we also compiled a list of terms frequently associated with each keyword (Table 2.2).

Table 2.2: Keyword selection

Keywords	**Commonly associated terms**
AI technology	Machine learning - deep learning - computer vision - neural network - ensemble learning - reinforcement learning
Resilience	Resilient - stability - stable - survive - survival - continuity - continue
Viability	Viable
Supply chain	Supply chain

As a result, we used a broad set of search terms in our search query as follows: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "neural network" OR "ensemble learning" OR "reinforcement learning") AND ("supply chain") AND (viability OR viable OR resilience OR resilient OR stability OR stable OR survive OR survival OR continuity OR continue). This initial search was performed on document titles, abstracts, and keywords, on 23 March 2024. We identified 780 documents for further analysis from the years 2007 to 2024, categorized as follows: articles (333), conference papers (254), conference reviews (100), reviews (44), book chapters (46), books (1), short surveys (3), retracted reports (3), and editorials (1). The year 2007 marks the publication of the earliest relevant studies that explicitly explored the application of AI in SC risk management, making it a suitable baseline for capturing the evolution of research in this domain.

Second, to rely exclusively on the most advanced research, we excluded conference contributions, book chapters, and editorials from the search process. Thus, we selected only documents published in journals: articles and reviews (377 documents containing 333 articles and 44 reviews).

Finally, we also excluded all articles (or reviews) not written in English (eight documents), thus obtaining 369 articles (or reviews) for the screening phase.

- **Screening and inclusion of documents**

We implemented a strict quality assessment method during screening which followed systematic literature review guidelines (Paul *et al.*, 2021). To substantiate our research, we considered only publications from reputable, high-impact journals based on two globally respected journal ranking systems: the Academic Journal Guide (AJG formerly ABS) from Chartered Association of Business Schools, and the Australian Business Deans Council (ABDC) journal ranking list. The AJG uses a five-level classification system that includes 4*, 4, 3, 2 and 1 rankings while the ABDC uses a four-tier system with A* and A followed by B and C. Our research included studies from journals which received at least a 2 for the ranking in AJG or at least B for the ranking in ABDC because these tiers usually represent good markers of academic excellence (Donthu *et al.*, 2021; Duan, Pang and Lin, 2023; Tchuente, Lonlac and Kamsu-Foguem, 2024).The ranking-based constraint helped maintain high methodological rigor and theoretical relevance among the included studies. Thus, this quality screening process resulted in 257 excluded articles which led to 112 high-quality articles for thorough examination.

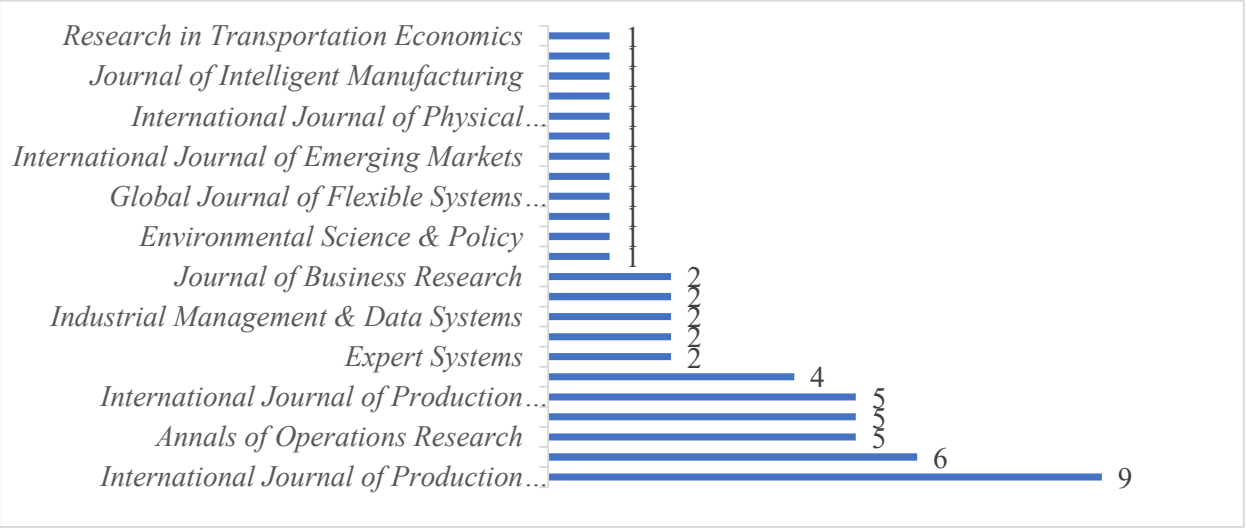


Figure 2.2: Distribution of journals by the number of articles

Second, to ensure that those eligible articles followed the requirements of our studies (AI application in SC resilience and viability), two of the study's authors manually checked the

abstract and full content of these 112 articles. We jointly agreed to exclude 45 studies due to inconsistencies between the research questions and objectives and the themes addressed, eight literature reviews, and three bibliometric studies. Thus, 56 articles were finally selected for the in-depth analysis of our topic. These articles are published in journals presented in Figure 2.

The final set of 56 journal articles included in this review reflects a deliberately focused and quality-oriented selection strategy. In addition to topic relevance, our inclusion criteria were restricted to articles published in journals well ranked in the AJG or ABDC journal quality lists, ensuring a high standard of scholarly rigor. This quality filter, combined with the specific scope of our study, yielded a focused corpus suitable for in-depth thematic synthesis. While broader literature exists on AI in supply chains, our research targets a specific and emerging subdomain where AI capabilities are explicitly applied to resilience or viability dimensions. As such, we adopted a quality-over-quantity approach, aligned with systematic review standards in the field. The sample size of 56 articles allowed for a thorough and in-depth qualitative analysis of each included study. This enabled us to extract detailed information, identify nuanced themes, synthesize findings effectively, and critically appraise the methodological quality of each paper, which would be considerably more challenging with an excessively large sample without sacrificing depth. Comparable systematic reviews on related topics often work with corpus sizes ranging from 20 to 70 articles, especially when topic-specific and quality-based filters are applied (Queiroz *et al.*, 2020, no date; Spieske and Birkel, 2021; Toorajipour *et al.*, 2021; Zamani *et al.*, 2023). Therefore, we consider the final sample of 56 journal articles as methodologically sound and sufficient to draw robust conclusions while maintaining a high level of academic quality.

2.3.2 Analysis of selected documents

To highlight the current gaps in the literature and suggest future research, the TCCM framework was used (Paul et al., 2019), where T stands for theory, C for context, C for characteristics, and M for methodology.

This framework helps to identify the widely used theories, constructs, and methods in research on the resilience and viability of SCs and provides new avenues for future research.

The TCCM framework is already widely used across various fields, including internationalization (Paul et al., 2019), loyalty programs (Chen et al., 2021), international cause-related marketing and innovation (Singh et al., 2022), bootstrapping and bricolage literature (Singh et al., 2022), the area of responsiveness (Bethune et al., 2022), or explainable AI

(Tchuente et al., 2024).

In this chapter, we aim to identify the key themes and research gaps in the application of AI technologies to improve the SCV and SCV.

2.4 Findings and discussion

This section synthesizes the 56 selected studies through the TCCM framework, aiming to move beyond mere categorization toward a deeper understanding of how AI enables SCR and SCV in disruption contexts. The Appendix presents more detailed descriptive findings (e.g., theories, characteristics, variables, and specific industries).

2.4.1 Theoretical foundations

The literature reveals prominently used theories like dynamic capabilities theory (DCT) (Cuong et al., 2022), fuzzy set theory (Hosseini et al., 2019), organizational information processing theory (OIPT) (Belhadi et al., 2021), resource-based view theory and causal theory (Roux et al., 2023) ***(See Appendix table A1)***. For instance, DCT has been successfully used in various practical applications to analyze the behavior of complex systems over time ***(See Appendix table A2).***

In developing new capabilities such as remote monitoring and telemedicine, firms can sustain continuity of care during a crisis. This adaptation is rooted in DCT, which emphasizes the need for continuous development and modification of capabilities to thrive in changing circumstances (Zamiela et al., 2022; Ekanayake et al., 2023).

Also, introduced by Zadeh (1965), the fuzzy set theory has been applied in many fields, such as the optimization of multi-objective problems and multi-criteria decision-making. In Shokouhyar et al. (2019), research primarily centers on designing and employing an expert system that utilizes fuzzy set theory to ensure information technology SC security.

Additionally, multi-criteria decision-making (MCDM) theory, employing linear programming, fuzzy set, and analytic network processes, has provided invaluable insights by evaluating different recovery strategies according to their effectiveness and feasibility (Deveci *et al.*, 2022). Furthermore, learning theory has underscored the importance of organizational learning and knowledge development for driving strategic adaptability.SC management research incorporates diverse data-driven theories that focus on collecting, analyzing, and utilizing information to enhance decision-making processes for efficient SC performance (Emrouznejad

et al., 2023).

2.4.2 Contextual Factors: Sector, location and risks

The manufacturing industry is the most common, studied in 12 articles, while the electronic and food industries are tied for the second most common industries.

The remaining industries (pharmaceutical and healthcare, energy, IT, automotive, energy, digital, maritime, nongovernmental organizations, digital, industrial automation, and services) have relatively lower counts (between one and four articles) ***(see Appendix Table A3).***

Among the 15 risk types identified **,** health-related risks emerge as the most studied (33%), primarily in response to COVID-19 (Ivanov *et al.*, 2023). This trend reflects a shift from traditional economic and logistical disruptions to those rooted in public health emergencies.

The next most prevalent categories are:

- Economic risks (16%), often tied to supply-demand mismatches and cost variability;
- Environmental risks (15%), reflecting sustainability pressures and climate-driven disruptions;

This typology supports a broader view of SCR that includes societal and ecological vulnerabilities, not just operational efficiency ***(See Appendix Table A5).***

2.4.3 Antecedents and Outcomes: Variables analysis

Across the corpus, AI adoption to ensure SCR and SCV is driven by both internal and external antecedents. Internally, technological readiness, data infrastructure, and top management support are prominent enablers (Ghadge et al., 2020). Externally, regulatory frameworks, pandemic urgency, and market complexity are frequent triggers for digital innovation (Sodhi & Tang, 2021).

Outcomes of AI integration span:

- Operational performance: e.g., forecasting accuracy, inventory optimization (Choi et al., 2022);
- Strategic outcomes: e.g., innovation capability, inter-organizational collaboration, and enhanced sustainability (Wamba et al., 2022).

This demonstrates that AI mitigates risk and acts as a strategic vector for long-term SCV.

According to Justin Paul (Paul et al., 2019), variables refer to the factors or characteristics that

are being studied or measured in the studied process.

To understand how different factors contribute to the success or failure of SC management, the scientific investigation must aim to categorize these elements into types based on their relevance and role in the study. In this chapter, we outline a grouping of factors into four different types: independent, dependent, moderating, and mediating variables ***(See Appendix Table A6).***

By synthesizing the diverse factors employed in empirical investigations concerning the application of AI with SCV and SCR, we can understand how scholars have measured and analyzed this field. Consequently, through a comprehensive synthesis, we can learn from the articles reviewed and provide information about the frequently used constructs/variables in prior research (see Table 9).

The categorization of variables into these types allows researchers to systematically analyze the relationships between them and gain an understanding of how specific factors impact desired outcomes. This is an extremely useful instrument for designing research studies, identifying critical variables, and interpreting results to draw significant conclusions.

2.4.3.1 Independent variables

Independent variables manifest when researchers manipulate them, expecting that they will influence another set of identified measurement indicators known as dependent variables (Abiodun-Oyebanji, 2017).

The systematic examination of the categorization of autonomous factors presents valuable insights into the multifaceted elements deliberated throughout the 56 analyzed articles in this investigation. These factors have been classified into six distinct groups: logistical, environmental, economic, healthcare, technological variables, and other, which, collectively, shape the dynamics of SC management.

Logistical variables span a range of transportation-related aspects, including the transportation medium, traffic patterns, storage temperature, and port capacity. These aspects provide valuable insights into the logistical aspects of SC operations, such as transportation efficiency and storage requirements (French *et al.*, 2017; Alam *et al.*, 2021; Dartnell and Kish, 2021).

The atmospheric conditions, such as ambient temperature, wind speed, atmospheric pressure, and humidity, are the major focus of environmental factors. In addition, climate-related factors, such as temperature, precipitation, and solar radiation, are taken into consideration by

researchers. Through the examination of these factors, researchers can obtain an understanding of the environmental challenges that affect SCR and SCV (Mamashli et al., 2021) ***(See Appendix Table A8).***

Economic variables cover a broad range of factors, such as historical sales data, assets, liabilities, cash flow, market demand, and control parameters like cost and implementation time. Additionally, evaluation criteria used to assess the sustainability performance of potential partners are included. These variables shed light on the financial and market-related aspects that significantly influence SC management decisions and performance.

Healthcare variables are specific to the healthcare industry and comprise variables such as records of therapeutic shipments collected pre- and post-COVID lockdown and the severity of a disaster (Mariappan et al., 2022). These factors highlight the distinctive considerations and challenges faced by healthcare SCs, emphasizing the need for targeted resilience strategies (Furstenau et al., 2022; Senna et al., 2023).

Technological variables are associated with the incorporation and utilization of advanced technologies within the realm of SC management. This includes the utilization of social media data from online SC forums, the application of deep RL algorithms, and various machine learning classifier models used to predict shipment times in e-pharmacy SCs (Mariappan et al., 2022). These variables underscore the growing significance of technology and AI-driven solutions in optimizing SC operations (Lin et al., 2022; Belhadi et al., 2021; Tian et al., 2024 ;Fosso Wamba et al., 2022). The categorization and analysis of these autonomous factors furnish researchers and practitioners with a comprehensive understanding of the multifaceted elements influencing SC management.

Other variables encompass a diverse set of factors unique to the specific context of the SC under study. These include sourcing policies and network structures, construction site parameters, product lifecycles, channel demands, organizational structures, and manufacturing process types. By considering these factors, researchers can explore the specific nuances and complexities of the SC being examined (Maghrebi, Shamsoddini and Waller, 2016; Bottani *et al.*, 2019; Suhail *et al.*, 2022).

2.4.3.2 Dependent variables

Dependent variables are those that depend on other factors that are measured and are expected to change as a result of experimental manipulation of the independent variable (Broughton, 2005).

Numerous variables have been identified by studies that contribute to the resilience and viability of SCs. These variables possess different characteristics and have different impacts on SC management, thereby classifying them into different types. Economic factors, among the studied variables, are particularly important and hold a direct impact on customer-perceived value, credit score (Yao et al., 2022), credit limit, and probability of default. The activity cost and execution time are economic variables that influence these factors. Moreover, decision support methodologies and forecast models, chosen by frameworks like UNISON (Fu et al., 2019), are critical economic variables for effective SC planning. Other variables of great significance include critical success factor theory, fluctuations in finished goods inventory and actual capacity (Cuong et al., 2022), lead time, total cost, order fulfillment rate, waste rate, partner classification, production rate, productivity, total profit, total lead time, user satisfaction, and total cost of tardiness ***(See Appendix Table A9).***

Logistic variables also play a crucial role, with logistics cluster activities in the food industry (Maffezzoli et al., 2022) speed and temperature settings of trucks, storage temperatures, and cargo temperatures inside containers are critical considerations. Additionally, environmental factors such as risk magnitude in disruption situations and temperature are relevant. Furthermore, healthcare variables such as shipment times of therapeutic supplies in e-pharmacy SCs (Mariappan et al., 2022) and frequency of occurrence of risk factors are also significant (Zaoui et al., 2023).

By evaluating and understanding these variables, researchers and practitioners can cultivate a comprehension of the intricacies and interdependencies present within SC management. This expertise has the potential to influence decision-making procedures and assist in formulating strategies to enhance the SCR and the SCV in the face of diverse challenges and disruptions.

2.4.3.3 Moderating variables

Moderating variables are variables that affect the strength or direction of the relationship between two other variables and specify when certain effects will hold (Baron et al., 1986).

The research results from the 56 articles yielded only 12 articles that included moderating variables.

We aim to shed light on how these variables impact the correlation between autonomous factors and the effectiveness of the SC.

In the context of SC management, the influence of multifaceted moderating factors assumes a

paramount significance as they intricately shape the complex landscape of decision-making processes and exert an impact on overarching performance outcomes. This acknowledgment underscores the need for comprehensive exploration and understanding of these moderating factors to advance scholarly knowledge in the field and inform strategic interventions for enhanced SCR practices. These factors include market values, grants, and manufacturing expenses ***(See Appendix Table A10).***

Additionally, the role of multiple stakeholders and climate conditions are important considerations (Kumar et al., 2021). For instance, weather patterns can significantly impact production, transportation, and storage, making climate conditions a critical mediating variable. Production expenses such as raw materials, labor, and operations also influence pricing strategies, competitiveness, and profitability.

Considering different variables, like market prices, subsidies, production costs, numerous stakeholders, and climate conditions, managers of the SC can create strategies that may improve the resilience, versatility, and efficiency of their operations. To maintain a seamless continuity of products and services throughout the SC ecosystem, it becomes imperative to establish and sustain fruitful partnerships with vendors, manufacturers, suppliers, distributors, and clients. This necessitates the development of effective collaborations that enable smooth coordination and cooperation among all stakeholders involved in the SC network.

2.4.3.4 Mediating variables

Mediating variables are variables that explain the relationship between two other variables, they are the mechanism through which one variable affects another (Baron et al., 1986). Out of the 56 articles examined, 21 articles were found to incorporate mediating variables (Belhadi et al., 2022; Mariappan et al., 2022; Gupta et al., 2023). These variables encompassed risk mitigation procedures, AI transparency and agile decision-making, and IC to mediate the relationship between agility, resilience, and performance in the humanitarian SC.

Additionally, intermediary factors such as corporate attributes (age, size, ownership, industry types), internal discretionary resources, managerial roles, external business environment factors were considered ***(See Appendix Table A11).***

2.4.4 Methodological factors

Effective analysis methods are a prerequisite for understanding and enhancing SC behavior, and the availability of data and computing power facilitates more sophisticated forecasting

methods. In this section, we outline a comprehensive review of previous research methodologies employed in the application of AI to SCR and SCV. The range of exploration approaches employed includes qualitative exploration, quantitative exploration, experimental research, and case studies.

Qualitative research methods have been instrumental in comprehending SC stakeholders' subjective experiences, perceptions, and behaviors concerning AI applications in SCR and SCV. These methodologies utilize conversations, group discussions, and thematic assessment to acquire an understanding of the difficulties, possibilities, and consequences of its adoption.

Quantitative research plays a crucial role in evaluating the impact and effectiveness of AI solutions in SCR and SCV. Data mining, modeling, and statistical analysis methods are implemented to measure the advantages, hazards, and performance enhancements linked to the introduction of AI. Quantitative research uses statistical techniques and analysis of large datasets to offer empirical proof for supporting decision-making and strategic planning.

Experimental studies have also evaluated the efficiency and capabilities of AI algorithms and technologies in SCR and SCV. These investigations require the development and execution of controlled experiments to contrast the efficiency of AI-based resolutions with conventional techniques. By manipulating variables and measuring outcomes, experimental studies contribute to understanding the potential of AI in enhancing resilience and viability in SCs ***(See Appendix Table A12).***

Case studies offer a holistic view of AI applications in real-world SC contexts. These studies provide in-depth analyses of specific organizations or industry sectors, examining the challenges faced, AI implementation strategies, and the outcomes achieved. Case studies commonly utilize both qualitative and quantitative data collection methods to grasp a comprehensive understanding of the AI adoption process and its impact on SCR and SCV.

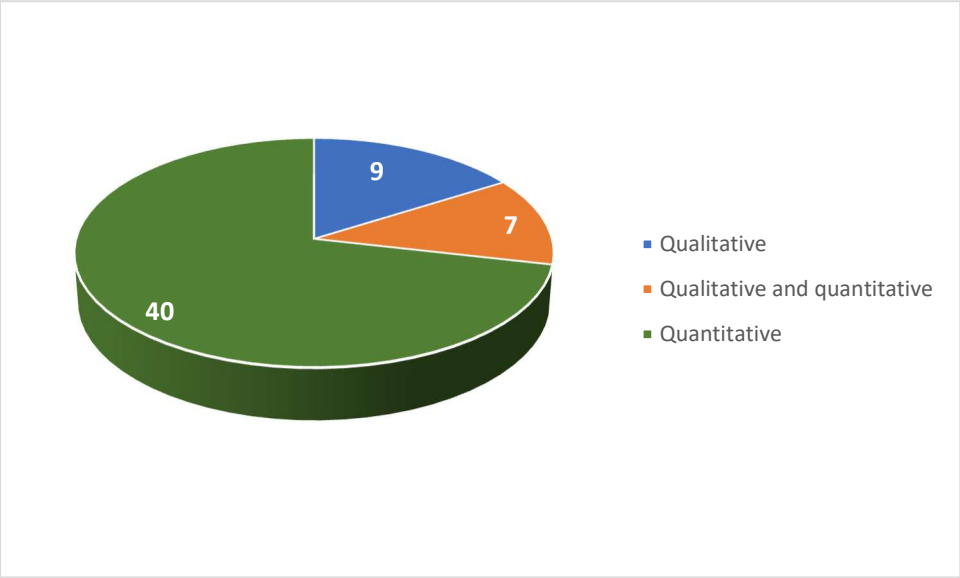


Figure 2.3: Research approach trends examined in this research.

2.4.5 Reflection on the literature

This chapter reviews the use of AI technologies in enhancing SCR and SCV. It provides insights into the prevalence of AI across various industries, their geographical distribution, and the significant challenges faced. It explores the application of different theories in the context of AI technologies to improve the understanding of SCR and SCV. Theories such as DCT, fuzzy set theory, causal theory, transaction cost economics theory, OIPT, and resource-based view theory are among the frameworks employed to address uncertainty, minimize transaction costs, facilitate trade and investment, and foster continuous development to adapt to changing circumstances. The findings reveal a diverse range of theories employed to address risks across different industries, as summarized in Figure 2.4.

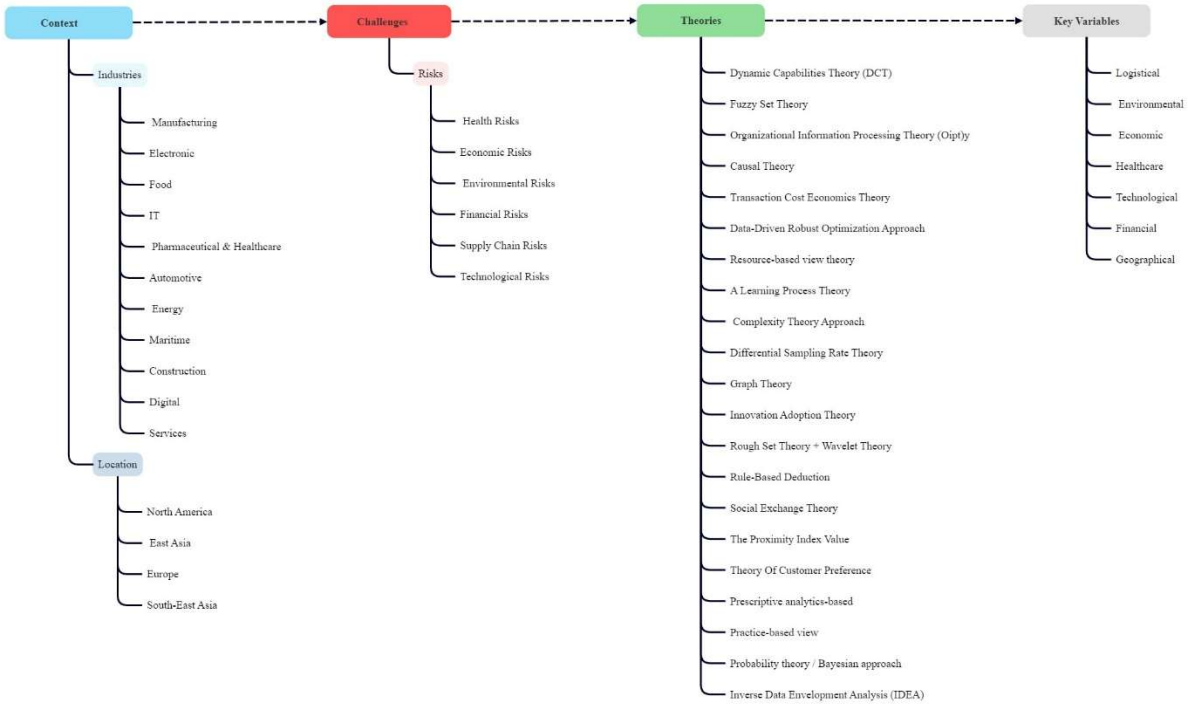


Figure 2.4: Research on AI in SCR/SCV

By relying on the TCCM protocol, we have identified the characteristics of AI applications in SCR, including the context, methods, and theoretical frameworks used. Antecedents refer to risk factors that influence SCR and SCV. Outcomes include SCR, sustainability, efficiency, performance, adaptability, optimization, risk management, innovation, collaboration, and transparency. Variables are classified into independent, dependent, moderating, and mediating variables. Independent variables include economic, environmental, logistical, healthcare, technological, and other factors. Dependent variables encompass forecasted demand, lead time, total cost, order fulfillment rate, waste rate, production rate, productivity, and total profit. Mediating variables include market prices, subsidies, production costs, the role of multiple stakeholders, and climate conditions. Moderating variables can impact the relationship between other variables. Independent variables are grouped into economic, environmental, logistical, healthcare, technological, and other categories. Additionally, a range of AI technologies, including neural network prediction controllers, machine learning, deep reinforcement learning, fuzzy set theory, and genetic algorithms, are employed to implement practical solutions, as summarized in Figure 2.5.

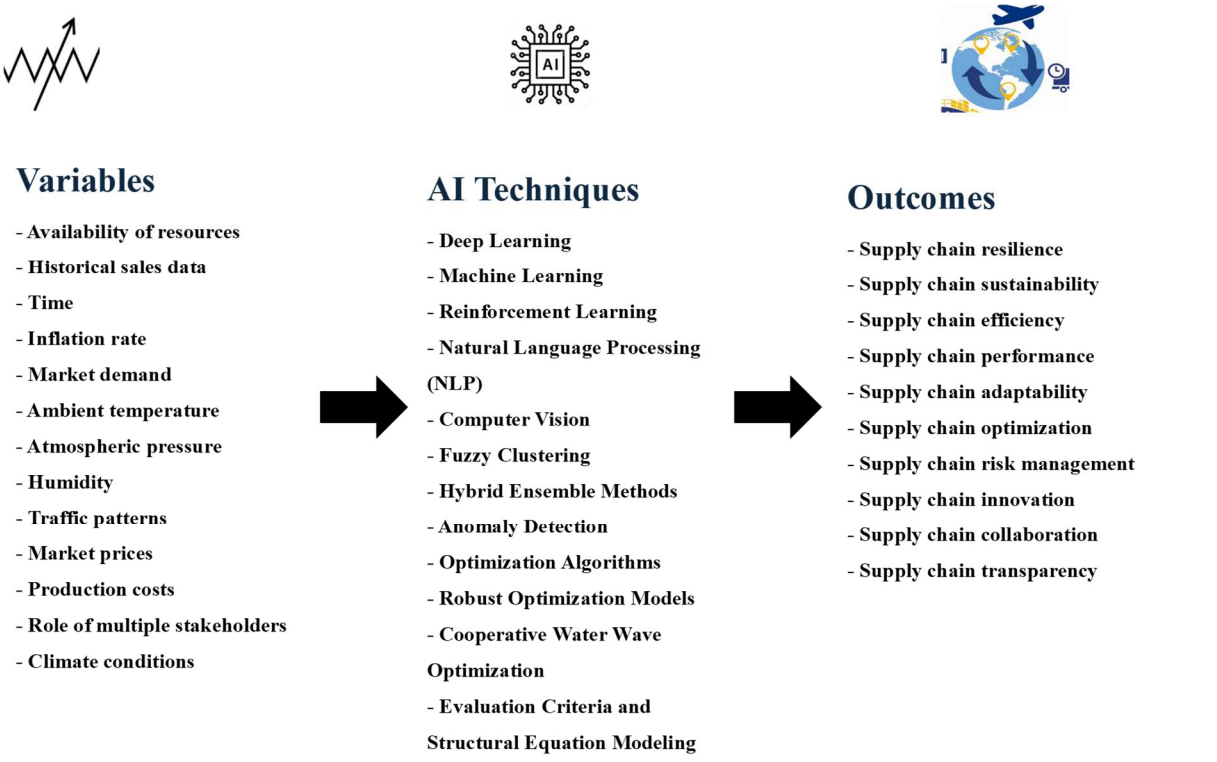


Figure 2.5: Variables considered via AI techniques and their resulting outcomes

In the field of SC management, various challenges are addressed through the application of specific theories and AI technologies (Rahman et al., 2022). These challenges include healthcare risks driven by the impact of the COVID-19 pandemic (figure 2.6), economic risks driven by urbanization, consumer demand, and e-commerce growth (figure 2.7), technological risks (figure 2.8), and environmental (figure 2.9) and financial risks (figure 2.10).

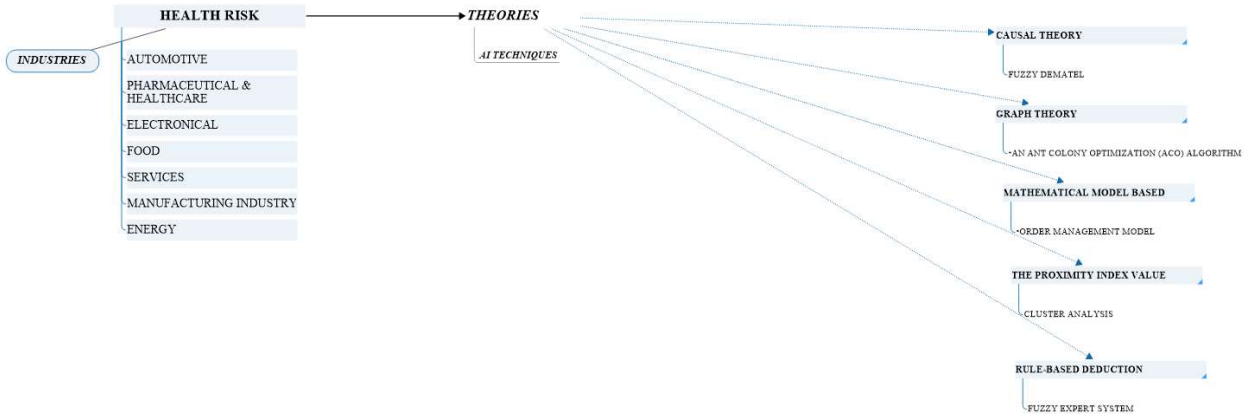


Figure 2.6: Theoretical approaches addressing health risks across industries and the integration of AI methods

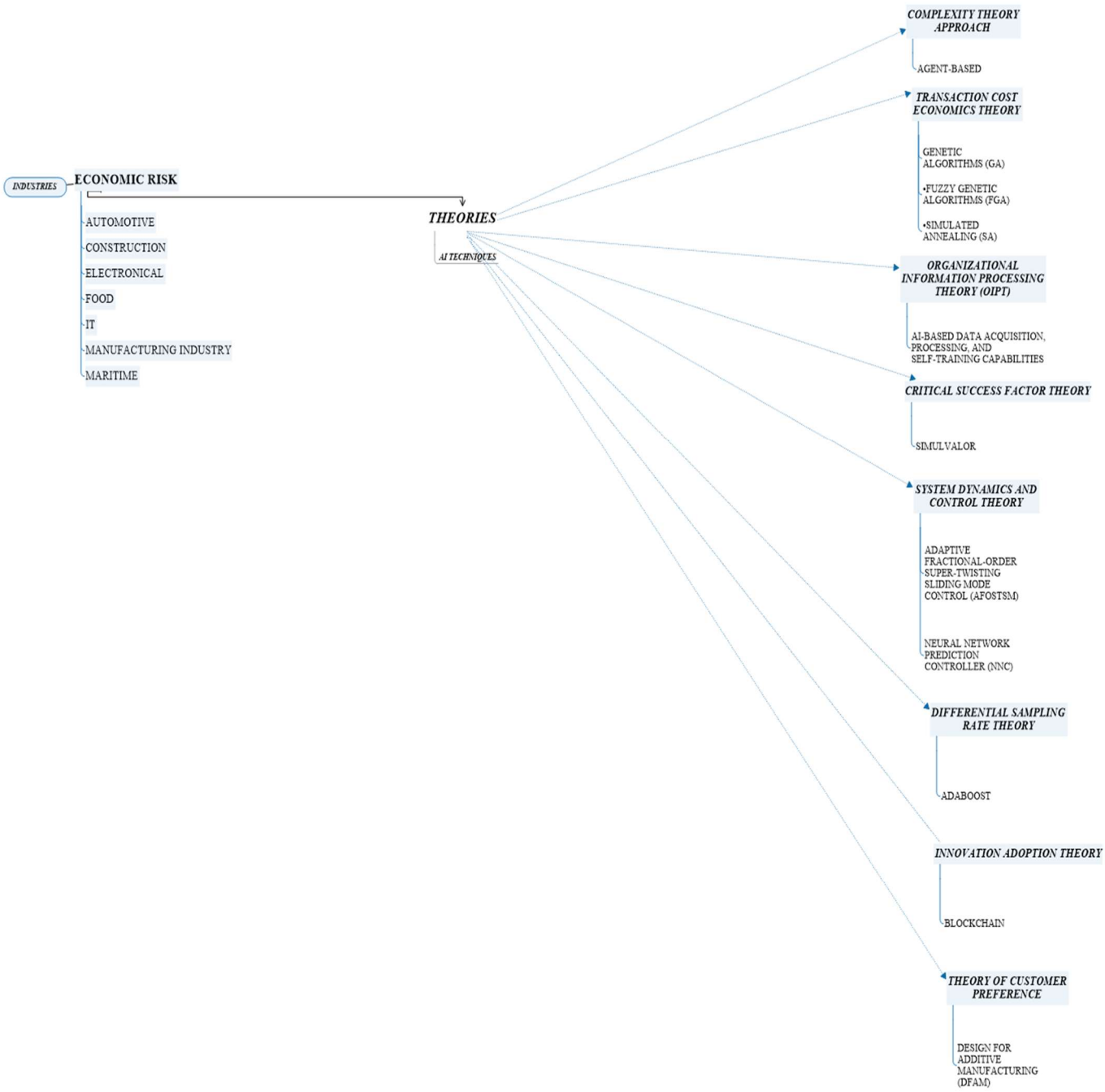


Figure 2.7: Theoretical approaches addressing economic risks across industries and the integration of AI methods

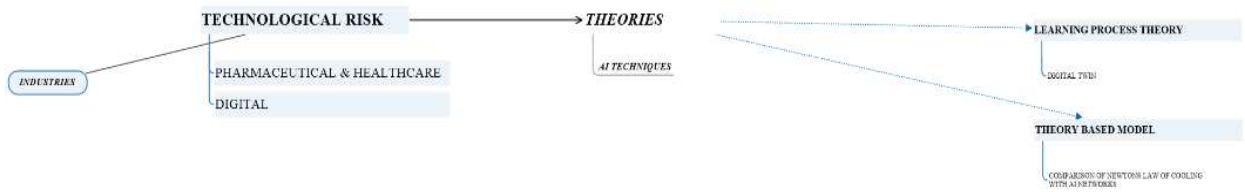


Figure 2.8: Theoretical approaches addressing technological risks across industries and the integration of AI methods

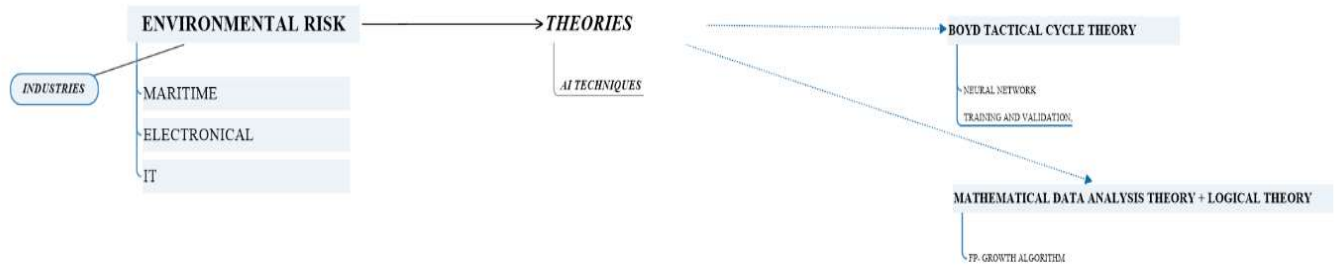


Figure 2.9: Theoretical approaches addressing environmental risks across industries and the integration of AI methods

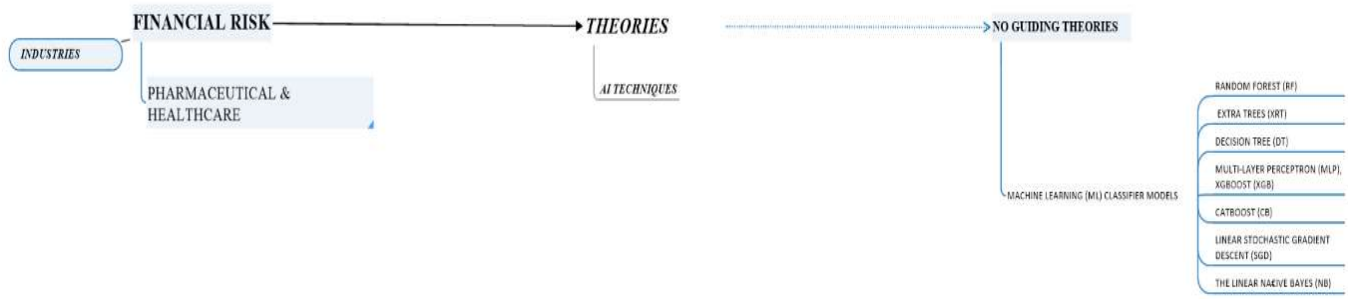


Figure 2.10: Theoretical approaches addressing financial risks across industries and integration of AI methods

2.5 Implications and future research avenues

2.5.1 Practical implications

The study offers practical contributions by demonstrating how AI technologies can enhance SCR across various industries. It identifies manufacturing as the most prominent sector for AI applications (Santos et al., 2018), followed by the electronics and food industries (Bechtsis et al., 2022; Bottani et al., 2019). Despite this, our findings indicate that no particular geographical region dominates the research landscape, suggesting substantial untapped potential for AI-driven improvements in SCR and SCV in diverse global contexts.

To support practitioners, this research presents several actionable implications. First, organizations operating in high-risk environments such as healthcare, electronics, and agri-food should consider adopting AI tools for real-time risk detection, predictive analytics, and demand forecasting. Second, managers are encouraged to implement AI-based scenario modeling to better anticipate disruptions and dynamically adjust SC's operations. For instance, firms exposed to economic or environmental uncertainties can deploy machine learning models to optimize inventory levels and logistics pathways under stress conditions. Moreover, the study highlights the importance of classifying risk types: health (Figure 2.6), economic (Figure 2.7), technological (Figure 2.8), environmental (Figure 2.9), and financial (Figure 2.10) as a foundation for selecting tailored AI strategies. This risk typology allows SC's professionals to assess their vulnerability profile and align AI tools accordingly. Each arrow in the visual framework presented in this chapter represents a specific relationship between a risk type, an AI technique, and a targeted outcome, thus serving as a practical decision-support tool for managers.

Finally, we recommend that companies establish cross-functional AI task forces that integrate data science, operations, and risk management teams. These teams can spearhead the implementation of AI-driven solutions aimed at improving efficiency, collaboration, risk mitigation, and long-term sustainability in SC's logistics (Kumar et al., 2021). By doing so, organizations can build resilience and transform their SCs into more agile and future-ready systems.

2.5.2 Theoretical implications

The research contributes to the theoretical apprehension of utilizing AI to ensure SCR and SCV. The research combines a variety of scholastic theories, including fuzzy set theory, transaction cost economics theory, OIPT, and DCT to create a study conceptual structure for tackling the

difficulties encountered in SC management. These theories offer insights into uncertainty management, minimizing transaction costs, facilitating trade and investment, and fostering continuous development to adapt to changing circumstances. The study's theoretical foundation enables researchers and practitioners to approach AI implementation in scs from a well-informed perspective, enhancing the potential for effective decision-making and performance improvement.

DCT, a prominent element among the discussed theories, has been successfully used to analyze the behavior of complex SCs focusing on enhancing flexibility in addressing unfamiliar events and uncertainties within dynamic environments. This flexibility plays an important role in achieving SCR, as it allows organizations to promptly adapt their operations and resource allocation in response to disruptive events (Demartini et al., 2019).

Through the utilization of a fuzzy set, institutions can grasp and articulate the intrinsic uncertainty and imprecision that frequently characterize actual SC data (Queiroz et al., 2020). This methodology enables more complex decision-making processes, where the traditional binary logic may be inadequate. In situations of uncertainty, such as abrupt demand fluctuations or unforeseen disruptions in the SC, a fuzzy set empowers decision-makers to assign varying degrees of membership to diverse outcomes or variables, facilitating adaptive and context-aware responses (Queiroz et al., 2022).

In addition, the transaction cost economics theory plays a significant role in the optimization of SC processes. By utilizing AI technologies with this theory, organizations can systematically identify and analyze the transaction costs associated with their SC activities (Halgamuge 2021). Through the implementation of automation and the utilization of data-driven insights, companies can minimize these costs, which may encompass expenses related to procurement, transportation, and collaboration with partners (Guo et al., 2021).

Consequently, the integration of the transaction cost economics theory with AI contributes to the effective management of the SC, thereby enhancing SCR by ensuring the efficient and transparent allocation of resources.

OIPT is an imperative perspective in the context of SCR and SCV (Belhadi et al., 2021). Through the utilization of AI technologies, this theory enables organizations to accumulate, process, and exploit substantial quantities of data that are generated throughout the entirety of the SC. AI-driven data analytics tools can sort through this data, extracting valuable insights that can serve to inform strategic decisions (Behl et al., 2022). Enhanced information processing

leads to an improved state of SCV as organizations acquire a more comprehensive understanding of their SC's present condition, potential risks, and opportunities (Reyes, Mula and Díaz-Madroñero, 2023). During times of disruption, possessing access to current information and advanced analysis enables organizations to rapidly make efficient decisions, thereby decreasing the impact of disturbances and improving the resilience of the SC.

2.5.3 Future research avenues

The breadth of our study's findings allows us to highlight eight key research and practical challenges that merit further investigation to enhance the use of AI technologies for SCR and SCV.

These directions are directly derived from the gaps and trends observed in our results and are presented below as highly potential areas for future research.

First, our study reveals that most of the included works focus on well-established AI techniques such as machine learning for demand forecasting or inventory optimization. However, there is little evidence of the adoption of more innovative AI applications specifically designed to address emerging and complex supply chain risks. Future research should examine the relevance and impact of advanced techniques such as digital twins, generative AI, or reinforcement learning in identifying and mitigating supply chain vulnerabilities. These methods may be particularly valuable in dynamic or high-uncertainty contexts, which were shown to be underexplored in our corpus (see figure 2.5).

Second, although our review identifies ethical concerns surrounding the integration of AI into supply chains, particularly in relation to decision automation and data governance, very few articles engage in an in-depth analysis of these issues. In light of growing societal expectations and regulatory frameworks, it becomes increasingly important to explore the ethical implications of AI implementation. This includes ensuring transparency, accountability, and fairness across AI-assisted supply chain operations.

Third, while several studies mention the capacity of AI to improve real-time decision-making, few works provide empirical evidence on how AI systems contribute to supply chain adaptability in the face of major disruptions such as pandemics or natural disasters. Given the increasing frequency of such events, future research should investigate the role of AI in enhancing flexibility, agility, and dynamic reconfiguration of supply chains under crisis scenarios. This gap is particularly notable in the context of health and environmental risks,

which emerged as significant yet insufficiently treated dimensions in our review (see Figure2. 6).

Fourth, the review shows a strong emphasis on reactive strategies for risk management, with limited consideration for proactive or predictive disruption assessment. Although predictive analytics are often mentioned, comprehensive frameworks for the early identification and mitigation of systemic risks remain scarce. Future studies should focus on developing robust models that combine risk sensing, scenario planning, and real-time data integration to anticipate and absorb potential shocks more effectively.

Fifth, while collaboration and stakeholder engagement are frequently cited as key drivers of resilience, very few articles analyze the concrete role of AI in facilitating such collaboration. Future research should examine how AI-enabled platforms and decision-support systems can foster coordination, transparency, and trust among supply chain partners. This could include the study of blockchain-based systems, multi-agent systems, or collaborative dashboards that enable shared visibility and risk-sharing mechanisms.

Sixth, although some contributions discuss supply chain redesign as a strategic option for resilience, little is known about the use of AI in supporting the diversification of supply chain configurations. In our analysis, centralized models remain dominant across most case studies. Research could thus investigate how AI can support the transition to more diversified, regionalized, or distributed supply networks, potentially reducing dependency and increasing redundancy across the value chain.

Seventh, while several articles link digital maturity and resilience, few studies provide a detailed evaluation of the financial or operational impacts of digital investments in supply chain transformation. As investment in AI remains resource-intensive, future research should aim to quantify the return on investment and assess the cost-effectiveness of various AI applications, especially in terms of recovery speed, service level improvements, and operational stability in disrupted environments.

Eighth, our findings underline the importance of building long-term partnerships to strengthen SCR and SCV. However, the potential of AI technologies in cultivating and sustaining such strategic relationships remains largely unexplored. Research is needed to investigate how AI can enable partner alignment, long-term performance monitoring, and trust-building across multi-tier supply networks.

In summary, this chapter provides a comprehensive overview of how AI is currently used to support SCR and SCV. The proposed research directions aim to deepen the theoretical

foundations and expand the practical applications of AI in this field. By addressing the challenges outlined above, future studies could contribute significantly to the development of more robust, adaptive, and sustainable SCs.

2.6 Conclusion

This chapter aims to advance the understanding of leveraging AI technologies for the optimization of SC management across diverse industries. A detailed analysis of various risk classifications underscores AI's essential role in addressing challenges while fortifying the robustness of SCs. The visual representation provided serves as a valuable tool for unraveling intricate relationships within SC management, guiding the implementation of AI-driven approaches for improved efficiency, teamwork, hazard mitigation, and sustainability.

This research sheds light on practical applications across industries and establishes a robust theoretical foundation. It empowers decision-makers to unlock the full potential of AI in navigating the complexities of SC management for enhanced resilience and viability (Iftikhar *et al.*, 2023). In ever-evolving market environments, data-driven decision-making becomes crucial, supported by tools such as partner selection criteria, business impact analysis protocols, and SC scenario planning models. Investigating the relationships among various factors enhances the richness of the findings.

Integrating AI into SC management promises significant advancements in resilience and viability by fostering collaboration, identifying risks, and optimizing operational efficiency. The review highlights key elements, including partner selection, temperature monitoring in cold chains, and developing predictive models for achieving economic and sustainable outcomes.

In conclusion, the findings lay a robust foundation for decision-making frameworks that prioritize SCR and SCV. Decision-makers are encouraged to align with relevant theoretical frameworks, judiciously implement AI technologies, and engage in an iterative process of monitoring and refining strategies, all backed by empirical evidence and analytical insights. This comprehensive framework empowers leaders to navigate the intricate challenges of SC management, ultimately leading to more resilient, adaptable, and efficient SCs.

Despite meticulous efforts to eliminate bias, the methodological framework of literature reviews can still be susceptible to subjective influences. Although keywords are carefully selected, the search for articles might not capture the entire scope of relevant publications. Furthermore, the exclusive use of the Scopus database for keyword searches presents another

limitation. Nevertheless, Scopus is acknowledged as a premier repository of scholarly works (Thelwall et al., 2022). Furthermore, we deliberately focused on ensuring the quality of the sources by selecting articles only from reputable journals, identified through internationally recognized rankings. This methodological rigor gives us confidence in the robustness of our findings. In addition, while the present systematic literature review includes 56 selected articles, which may be perceived as a potential limitation in terms of scope, this number aligns with several existing systematic reviews published in high-ranked journals, when relying on rigorous selection criteria that ensure depth over breadth (Tchuente et al., 2024; Smyth et al., 2024; Vishwakarma et al., 2024; Pourhabibi et al., 2020). However, we acknowledge that future research could adopt alternative approaches by employing different keywords, additional databases, or broader selection criteria. Despite these potential methodological constraints, the findings of this chapter offer valuable contributions to both theory and practice. They also underscore several research and practical challenges that warrant further investigation to advance the effective use of AI technologies in SCR and SCV.

Chapter 3

The Viability of Supply Chains with Interpretable Learning Systems: The Case of COVID-19 Vaccine Deliveries

ABSTRACT

The main objective of this chapter is to examine the instrumental role played by interpretable learning systems, specifically artificial intelligence (AI) technologies, in enhancing supply chain viability and resilience. It seeks to contribute to our understanding of the critical role played by interpretable learning systems in supporting decision-making during emergencies and crises. The research employs an empirical approach to address the research gaps in the application and impact of interpretable learning systems in supply chain management by utilizing the case of COVID-19 vaccine deliveries in France as a descriptive study. The findings highlight the ability to develop a learning system that adeptly predicts vaccine deliveries and vaccination rates. It emphasizes the importance of interpretable learning systems in optimizing supply chain management, navigating the complex landscape of vaccine distribution, establishing effective prioritization strategies, and maximizing the efficient utilization of resources.

Keywords: Artificial intelligence; COVID-19; Flexible supply chain; Interpretability; Machine learning; Risk prediction; Viability

3.1 Introduction

Supply networks function as the fundamental framework of our economic and societal construct, linking providers, producers, production hubs, distribution hubs, and storage facilities (Wagner et al., 2015; Bozarth et al., 2009) propelling operational effectiveness by amalgamating ecology, community, and commerce (Joshi, 2022). However, the resilience of these networks in the face of disruption or uncertainties and their ability to recover swiftly through reactive contingency plans, such as a risk mitigation inventory or backup sources, is crucial (Ivanov et al., 2019).

The COVID-19 pandemic affected all strata of society across the world. The spread of the pandemic, which was exacerbated by human contact was due to the transmissibility of the COVID-19 virus (SARS-Cov2), the significant morbidity and mortality that this disease caused, and the absence of effective treatment. Therefore, global vaccination of the majority of the population became a crucial measure to combat COVID-19 infection. Achieving herd immunity through vaccination was a top priority for all countries to reduce the toll of COVID-19 on the global economy and health. However, managing the delivery of COVID-19 vaccines presented a challenge due to their limited shelf life and specific storage and freezing conditions. Therefore, seamless and efficient planning was imperative to ensure the sustainability of supply chains to transfer valuable doses to vaccination centers for a successful vaccination campaign. The COVID-19 vaccine supply chain must be followed from start to finish, requiring heightened security to ensure its viability. The administration of vaccines to target populations, which is the last stage of the supply chain, remains the most complex and difficult to manage due to the many hazards it may encounter. The human parameter plays a vital role in securing the entire vaccination process and ensuring the viability of the COVID-19 vaccine supply chain (Patri et al., 2017). However, it can, at any time, disrupt the entire supply chain and generate uncertainties regarding the volumes of effects being prone to human error or negligence.

The global impact of the COVID-19 pandemic extended beyond public health concerns, causing widespread disruptions in businesses and revealing vulnerabilities in lead times, order quantities, network structures, and demand volatility. This crisis exposed the far-reaching extent of disruption propagation within global supply chains, affecting all sectors of the economy and society (Ivanov et al., 2019). Moreover, despite a wide adoption of AI technologies for improving the performance of supply chains in general, many recent systematic literature reviews on this topic show that the literature is still scarce concerning the

use of learning systems based on AI technologies for supply chains resilience and viability (Riahi *et al* 2021; Younis et al., 2022).

Consequently, researchers and supply chain stakeholders need new decision-making parameters to address these challenges, particularly in measuring resilience and ensuring the survival of companies through risk management mapping (Camara et al., 2017). For instance, severe disruptions can have a profound effect on the healthcare supply chain, considering the high stakes involved in the healthcare sector where human lives are at risk (Aldrighetti et al., 2019). Designing and planning more flexible and resilient healthcare supply chains should include consideration of disruption risk, particularly due to the rising frequency of catastrophic events in recent years (Hasan et al., 2023).

Pandemics introduce unprecedented fragilities and risks to supply chains, characterized by prolonged disruptions, ripple effects, and high uncertainty as observed in the COVID-19 outbreak. The unavailability of transmission links, distribution centers, suppliers, and manufacturing facilities poses significant threats to the design structure of supply chain networks, resulting in ripple effects, diminished productivity, and performance (Ivanov, 2020a).

In response to these challenges, Ivanov (Ivanov, 2020a) has already addressed the issue of supply chain viability by reviewing COVID-19 containment measures. Furthermore, (Dubey, 2023; Queiroz *et al.*, 2020) have demonstrated the potential of digital technologies to mitigate severe disruption risks during crises like pandemics, which can disrupt the smooth functioning of public and private services. (Ruel *et al.*, 2021) have noted how supply chain viability encompasses organizational functionalities that create a competitive advantage by facilitating rapid adaptation to super-disruptions.

Although the existing literature on supply chain management during pandemics has explored various aspects, there has been little investigation into the specific application and impact of interpretable learning systems based on AI technologies such as artificial neural network approaches (Ivanov et al., 2020). While recognizing the significance of resilience and viability, further research is needed to understand the implementation and influence of such technologies in improving the viability of supply chains during emergencies (Pagell et al., 2009). For example, the use of information communication technology can improve the efficiency of organ retrieval processes in the donation supply chain. It is important to consider disruption risk and plan for more flexible and resilient healthcare supply chains due to the increasing occurrence of disastrous events (Dhakate et al., 2020).

The research gaps identified in this chapter address three specific aspects: the potential of interpretable learning systems in supporting supply chain resilience, the role of interpretability and explainability of learning systems in enhancing supply chain viability, and the accuracy and effectiveness of artificial neural network approaches in predicting COVID-19 vaccine deliveries and vaccination rates. The limited research addressing these aspects highlights a gap in the literature, and in-depth empirical investigations are required to fill this knowledge void.

By highlighting these research gaps, it becomes evident that there is a need for further empirical studies that specifically examine the application and impact of interpretable learning systems based on AI technologies, such as artificial neural network approaches, to enhance supply chain viability during pandemics. Closing these gaps would provide valuable insights for the practitioners and decision-makers involved in supply chain management, enabling them to make informed decisions and effectively manage viability risks during crises.

This chapter aims to explore the role of interpretable learning systems, specifically AI technologies, in supporting supply chain resilience and ensuring the viability of supply chains during a pandemic crisis. It seeks to address the following research questions:

RQ1: How can interpretable learning systems, particularly AI technologies, effectively enhance supply chain resilience and ensure the viability of supply chains during a pandemic crisis?

RQ2: To what extent can the interpretability and explainability of learning systems be leveraged as strategic opportunities to bolster supply chain viability during disruptive events such as the COVID-19 pandemic?

RQ3: What are the implications of adopting interpretable learning systems approaches for accurately predicting COVID-19 vaccine deliveries and vaccination rates, considering multifaceted factors such as population demographics, storage areas, vaccine suppliers, and modes of transport?

These research questions aim to investigate the role of interpretable learning systems and AI technologies in strengthening supply chain resilience during pandemics, exploring the benefits of explainability and interpretability in enhancing supply chain viability, and assessing the importance of interpretable learning systems approaches in forecasting COVID-19 vaccine deliveries and vaccination rates. By addressing these inquiries, we aim to deepen our understanding of supply chain resilience, inform decision-making in crises, and provide practical insights for supply chain management practitioners and stakeholders.

To ground these theories in practice, we plan to present a descriptive case study focusing on COVID-19 vaccine deliveries in France, allowing us to gain valuable insights into the real-world applicability of the proposed approaches.

The structure of this chapter follows Saunders et al.'s research onion framework (Seuring et al., 2021). Section 2 provides the research methodology adopted. Section 3 presents a comprehensive overview of SCS and SCV, emphasizing the need for problematization and discussing the relevance of supply chain risk management (SCRM) and explainable artificial intelligence (XAI). Section 4 introduces the methodological framework for building viable supply chains. Section 5 details its development through a case study on COVID-19 vaccine deliveries in France, and Section 6 examines the application scenario for the vaccine distribution case in the Auvergne-Rhône-Alpes (ARA) region. Research findings are presented in Section 7, followed by a detailed discussion in Section 8. Finally, Section 9 concludes the study and highlights the implications of the findings for future research and practice.

3.2 Research Methodology

The methodology used in this chapter follows the structure as shown in Figure 3.1, starting with the state of the art, presenting a generic model/framework, conducting a descriptive case study, engaging in discussions based on the findings, and concluding the research with key takeaways and suggestions for further research.

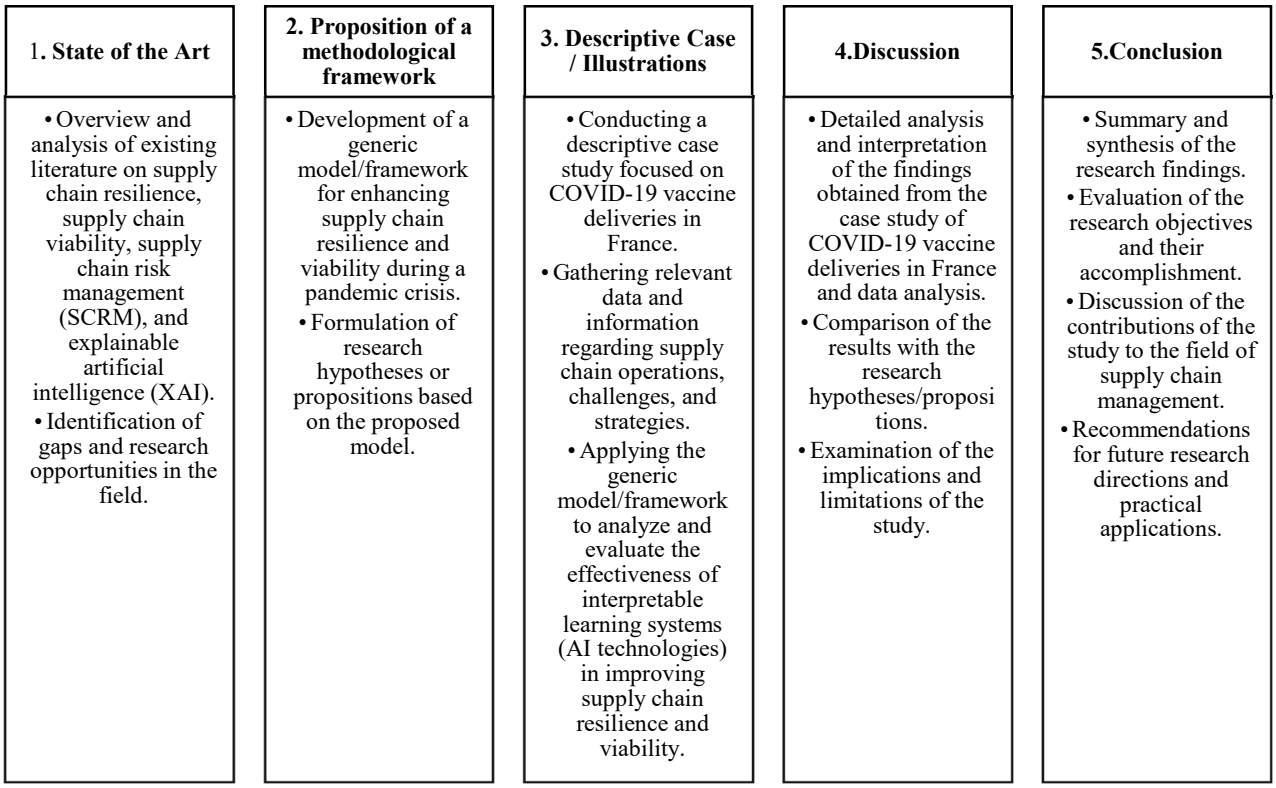


Figure 3.1: The research methodology

3.3 State of the art

3.3.1 Crisis management

A crisis describes a grave threat that directly impacts an organization's fundamental structures, core values, and norms. Such situations necessitate critical decision-making under immense pressure and uncertainty. A crisis is characterized by a jeopardizing of the primary objectives of the decision-making unit, the imposition of constraints on the available response time for transformational decisions, and decision-makers being caught off guard with its emergence.

Crises can manifest at various levels, including international, national, local, or organizational. They can be classified into several threat categories, such as environmental (e.g., natural disasters), industrial and technological, political, societal, human, sanitary (e.g., pandemic outbreaks like the COVID-19 pandemic), economic, image and information-related, communication-related, organizational, and IT-related, and strategic crises.

Managing crises involves making difficult and complex decisions in an environment marked by significant economic insecurity and uncertainty. To mitigate uncertainty and effectively navigate the complexities associated with crises, the involvement of expert advisers in the decision-making process plays a pivotal role (Merendino et al., 2020).

Disruptions resulting from crises inevitably have repercussions for societal well-being, irrespective of their geographical location. Therefore, it becomes imperative for organizations to adopt resilient practices. Specifically, organizations need to enhance their capability to detect low-intensity signals by implementing sensitive sensors and flexible processing mechanisms. These mechanisms should be capable of identifying and supporting the analysis and tracking of uncertain signals through interpretable learning systems.

Learning systems can serve as a point of reference, acting as a repository of knowledge for consultation. By utilizing previously collected data and implementing memory devices, access to previously analyzed cases can provide valuable initial benchmarks for crisis management.

Additionally, organizations should actively monitor "foreign" crises, which may not directly impact their supply chain but can offer valuable insights for future disruptions. This continuous questioning and examination of crises and difficulties contribute to proactive measures in confronting potential challenges (Holland et al., 2021).

Furthermore, mobilization should occur in stages, beginning with an active-standby setup that enables the timely initiation of the response efforts. As the situation evolves, the state of pre-alert may be lifted, maintained, or escalated to a higher level. Intense information exchange and accurate situation assessment through potentially active monitoring yield tangible results. Once the risk becomes evident, a serious alert is triggered, prompting a series of preparations within the supply chain (Sheng et al., 2021).

During severe disruptions such as the COVID-19 pandemic, we have seen imminent risks that severely impact the resilience and viability of the SC (Liu-Lastres et al., 2023).

3.3.2 The Concepts of Viability and Resilience

Most of the models and frameworks developed in the existing literature have not adequately addressed disruptions, resulting in a lack of appropriate strategies for companies to deal with them. These models often overlook the concept of viability, which is crucial for a supply chain's ability to maintain itself and survive in a changing environment through the redesign of structures and the replanning of performance with long-term impacts (Ruel *et al.*, 2021).

Developing business resilience requires effective continuity management processes and communication strategies (Hey, 2010). Sufficient time and resources are necessary for this process (Queiroz *et al.*, 2022), including financial allocations, staff education, and support from senior management.

The adaptability and flexibility of the SCs hold the ability to ensure the resilience of the supply chain, consequently securing the SC's performance. The association between SC's performance and both agility and flexibility appear to be mediated by SCR (Queiroz *et al.*, 2023).

The COVID-19 pandemic has highlighted the importance of sustainability in enabling SCs to cope with extraordinary events characterized by high health risks. During such crises, it becomes essential to consider the resistance of the SC to disruption at the scale of survival or viability. By doing so, chaos due to SC and market collapse can be avoided, ensuring the continued delivery of goods and services. Viability has been widely employed in bioeconomic modeling to denote the system's ability to maintain and recover in the presence of disturbances over the long term (Ivanov et al., 2020).

Viability is a behavior-based system property that accounts for structural dynamics and considers open system context. It recognizes the dynamic nature of the system and the importance of adaptive responses to disruptions. In (Saha et al., 2022), the behavior-based property of a system can be seen in how organizations adopt and implement Total Quality Management practices and I4.0 technologies to improve the system's behavior by promoting efficient processes, quality control, operational performance, and sustainability. Similarly, the integration of advanced technologies enables organizations to improve operational processes, optimize resource allocation, reduce energy consumption, minimize waste and pollution, and enhance safety measures. These behaviors demonstrate the system's ability to adapt and respond to changing market demands, technological advancements, environmental considerations, and disruptions.

Table 3.1: Differences between resilience and viability (Ruel et al., 2021)

Criteria	Resilience	Viability
System	Closed	Open
Structure	Static	Dynamic
Scope of analysis	Discrete events	Continuous change
Analysis subject	Discrete disruptions	The continuous evolution of adjustment
Analysis target	Performance-oriented	Survival-oriented
Analysis period	Fixed time window	Flexible time window
Object of analysis	Linear supply chain	Nested supply chains

The survival capacity of the SC in the context of such extraordinary events goes beyond a narrow understanding of the performance of the supply chain as benefits or revenues. It requires the transformation, or even adaptability, of production systems, including health risks and the adaptability of the production system oriented toward confronting the disruption; for instance, to solve the supply problems during the pandemic crisis in COVID-19. The suppliers of the automotive or aeronautical sector being able, at the same time, to become producers of valves for respirators is an example of another dynamism of performance; that is, the performance of logistics chains in terms of securing the supply of goods and services in society and the long-term survival of all industrial sectors.

3.3.2.1 The viability of the supply chain

The COVID-19 pandemic highlighted the importance of resilient supply chains and the challenges in overarching systems like communication, mobility, and healthcare (Ivanov, 2020b). Viability, a key aspect, involves surviving disruptions and demands adaptable network structures for effective supply-demand management based on situational criteria. Transitioning between these designs is crucial for success (Ivanov, 2020a). Algorithms need interpretability and transparency for consistent workflows.

Viability depends on stability, robustness, and resilience:

- Stability: Reverting to a pre-disturbance state for continuity

- Robustness: Tolerating disturbances without compromising performance.
- Resilience: Coping and recovering from disruptions.
- Viability: Sustaining in changing environments through economic replanning and structural redesign

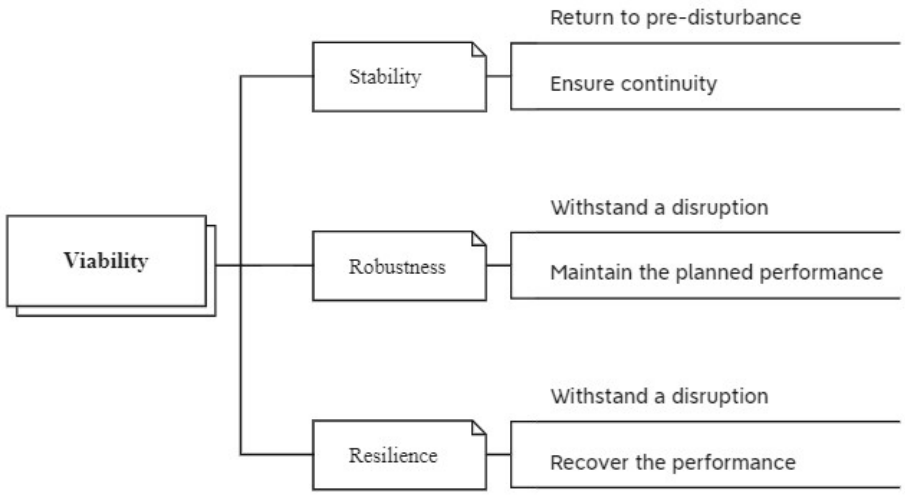


Figure 3.2: Viable supply chain characteristics (Ivanov et al., 2019; Ivanov, 2020b)

3.3.2.2 The resilience of the SC

The enhancement of SCR can be achieved by developing essential proactive and reactive capabilities and ensuring the quality of supply chain design. SCR is characterized as a multidimensional and hierarchical construction encompassing three primary dimensions: proactive capacity, reactive capacity, and the quality of supply chain design. Decision-makers stand to benefit by focusing on developing these proactive and reactive capabilities and ensuring a high standard of design. Therefore, it is imperative to implement upstream adapted strategies during the design phase of a SC. The proactive and reactive natures are key factors in developing a supply chain's resilience through preparedness for disruptive events, response, and recovery capacity during the pre-crisis and post-crisis phases to avoid a discontinuity of the SC thus affecting the revenues and costs of the entire chain. The results show that SCR is a multidimensional and hierarchical construct consisting of three main dimensions: proactive capacity, reactive capacity, and the quality of supply chain design (Chowdhury et al., 2017).

Resilience is the central perspective of SCV, thus ensuring the viability of the SC in the future. We note two major characteristics of SC resilience:

- ***Proactive:*** flexibility, visibility, redundancy, integration, financial strength, and market capacity.
- ***Proactive and reactive aspects:*** flexibility, redundancy, agility, recovery time, cost, and response effort. Supply chains require proactive and reactive capabilities to adapt, integrate and reconfigure during the pre-disruption and post-disruption phases.

The emergence of nested supply chain viability as a critical and timely topic introduces new problem parameters and solution techniques. The global pandemic and the subsequent collapse of supply chains have propelled discussions on risk management, prioritizing the survival challenges SCs face due to collective behavioral changes (Ivanov, 2020a).

In response to these challenges, (Rahman et al., 2020) propose behavioral and operational approaches to address distorted demands, enhance production and inventory management, and introduce a methodology for quantifying the intensity of the bullwhip effect, order fluctuations and demand quantity. They consider seasonal variations and associated strategies in their efforts to shift risk management conversations toward effectively tackling the specific challenges faced by supply chains during the ongoing pandemic and the potential risks of system collapse.

For example, the implementation of the 5S methodology can help management build a secure, healthy, and safe working environment while ensuring compliance with standards, leading to quality improvement within the organization (Sorooshian *et al.*, 2012). The organization can proactively reduce waste and improve productivity by reducing assembly line cycle time, searching time for tools, and improving workplace safety. Additionally, employee motivation and training play critical roles in the success of 5S implementation and serve as an example of reactive capacity in achieving SCRE. This suggests that the organization has the necessary reactive capacity to respond to unexpected events that may impact its SC (Shahriar *et al.*, 2022).

Indeed, the application of digital technologies to increase the resilience ability of a SC in a pandemic context is important. Particularly with a focus on data analytics, AI, and machine learning (Choi et al., 2017). This significance extends beyond the eatery industry, as highlighted by (Talapatra et al., 2022), where the two principles identified can be replicated in the field of SCRE. In this context, managers must ensure the adoption of proposed technological solutions to address the dynamic economic landscape that can disrupt user expectations. By integrating customer satisfaction factors into conceptual frameworks, organizations can leverage them to contribute to the improvement of SCR and viability. Using digital twins improves demand forecasting through data analysis, additive manufacturing flexibility, and SC visibility. Moreover, digital twins (Ivanov et al., 2019) can be used to anticipate interruptions by visualizing an SC's risks, predicting the various interruptions that will be triggered and directing the SC toward alternative supply networks.

By using real-time data, digital twins can simulate the impacts of disturbances on SC and propose alternative SC designs not affected by disturbances based on real-time inventory, demand, and capacity data.

The concept of resilience goes hand in hand with the viability of SCs: Among the major aspects of the resilience of an SC are its ability to withstand disturbance and ripple effects and recover, and de facto, it develops its viability through its ability to maintain and survive in an ever-changing environment (Ivanov, 2020b).

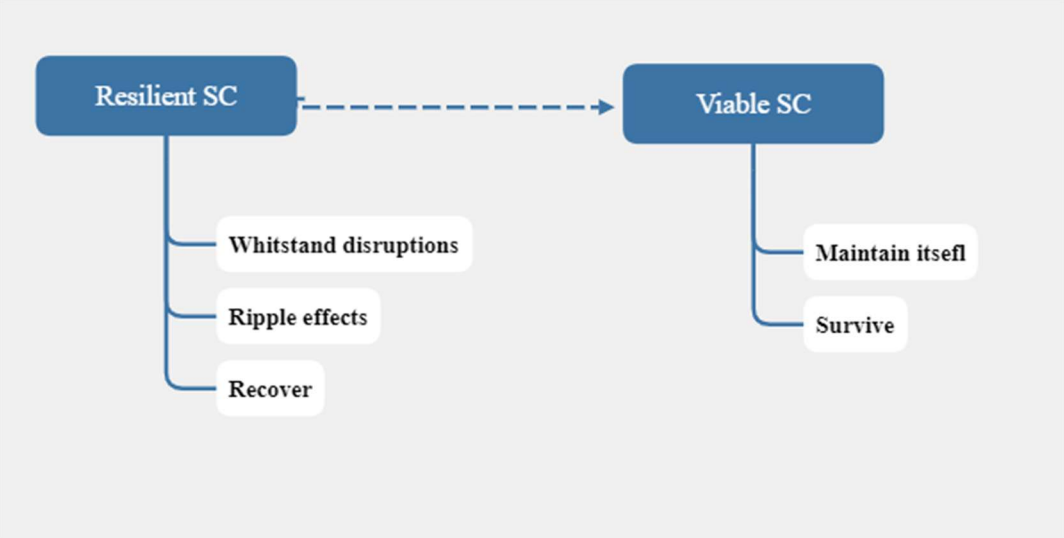


Figure 3.3: Resilient SC and viable SC characteristics

3.3.2.3 Resilience and uncertainty type

Managing the resilience of SCs is necessary to contain the effects of a long-term crisis such as the COVID-19 pandemic. Indeed, predicting the impacts of the pandemic on SCs (Chowdhury et al., 2017; Dubey, 2022; Ivanov, 2020b; Singh, 2020), an analysis of operational responses and supply chain performance during the pandemic and the post-pandemic recovery (Ivanov and Dolgui, 2021b) are the main research topics. The SC's resilience is the ability to bounce back from disruptions. We will present the distinctive characteristics of SCs in the case of a profoundly uncertain environment and the case of an epistemic environment, thus concluding with the idea of (Ivanov, 2021a), which consists of viability as a perspective of extended resilience.

a. Uncertainty type: Epistemic and Hazard



Figure 3.4: Resilience management in epistemic uncertainty

b. Uncertainty type: Deep

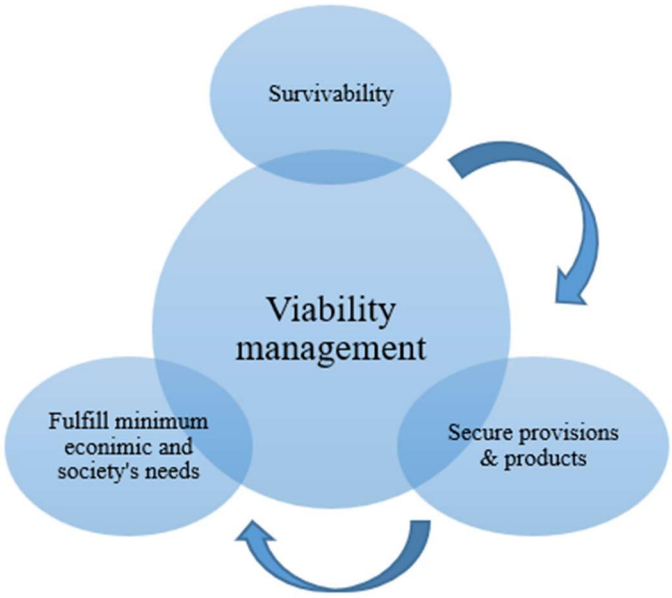


Figure 3.5: Viability management in deep uncertainty

Modeling the different reactions of SCs to disruptions through the use of digital twins and the proactive application of resilience analysis will ensure the survival of society in the face of crises such as the COVID-19 pandemic (Ivanov et al., 2021b).

Pandemic outbreaks spread quickly across various areas and impact the global SC's system (Ivanov et al., 2020). Adaptation was often the only way to survive (Ivanov, 2021b).

Figure 3.6: Major components of SC risk in a pandemic context (Ivanov et al, 2019).

3.3.3 Challenges for Controlling Logistics

Supply chain risk management (SCRM) researchers are exploring AI's potential in tasks like risk identification, prediction, evaluation, and response (Er Kara et al., 2020; Wever et al., 2022;). However, current research is either largely theoretical without real-world implementation (Chu *et al.*, 2020), or offers case-specific solutions (Fan et al., 2017). Machine learning complexity and lack of interpretability raise concerns over decision-making confidence.

An interpretable algorithmic decision is one that is explainable based on known data and situational factors. It links variable values to forecasts, scores, and decisions. Conversely, an explicable decision reveals factors affecting the decision method and their magnitude (Wamba-Taguimdje *et al.*, 2020). In (Christoph Molnar, 2020), the authors outlines reasons that support the importance of interpretability, with certain points being pertinent to SCRM:

Extracting knowledge captured by ML models.

- Identifying model bias.
- Enhancing solution acceptance.

In the SC's context, AI results must be interpretable and justifiable for meaningful integration into SCRM decision-making. Decision-making's evolution involves data analysis encompassing cognition, prediction, prescription, simulation, machine learning, reinforcement, and DNNs (Sassanelli et al., 2022).

3.3.3.1 SCRM and AI

A SC is an intricate network of organizations, including upstream and downstream connections, that enables diverse processes leading to end consumer product and service creation (Riahi *et al.*, 2021a). To manage SC's risks, a coordinated and unified approach among partners is vital. This recognizes and mitigates risks, thus bolstering SCR (Jüttner, 2005).

Moreover, the SCRM is positively associated with reducing supply chain risks. In a complex and large supply chain, risk management faces the challenge of identifying all potential risks and hazardous events, making it difficult to achieve its objective. As a result, risk management can enhance the resilience of the supply chain, yet it does not effectively address all resilience-related issues within the supply chain (Pettit et al., 2010). However, SCRM continues to be an intriguing field of application for AI. By utilizing resilient strategies that involve real-time decision-making and reactivity based on multidimensional data sources, SCRM could further reinforce the resilience of the SC.

For a rapid assessment and effective minimization of risks or disruptions that may affect an SC, the application of AI is an innovation that could improve and optimize the ability of the supply chain to overcome the problems below. AI plays a significant role in optimizing SCs and strengthening their resilience, making it possible to cope with their increasing complexity by processing and analyzing large data through machine learning, natural language processing, and robotics, for example. The use of AI helps us to understand and expect the impact and predict the occurrence of an SC disruptive event, such as the COVID-19 pandemic. By using algorithms, AI can clearly, accurately and quickly identify large data with which to develop a model that allows decision-makers to better understand how each process works, identify the factors that affect an SC's performance, and help managers predict performance or risks. Indeed, AI techniques such as Iot sensors in SCs are increasingly improving and enriching decision

support through data analysis, data trend detection, forecasting, and anticipation (Hemmati-Sarapardeh *et al.*, 2020).

However, AI and machine learning play a key role in demand forecasting and thanks to the increased use of smart equipment, SCs are becoming smarter and more efficient. In addition, the use of AI-based models in transport makes it possible to solve routing problems with a guarantee of on-time delivery to respond effectively to customer requests through the implementation of automated storage solutions or robots, operators assisted by handling equipment or the exploitation of traffic data in real time (Riahi *et al.*, 2021a). The potential of AI-driven large-scale data analysis serves as a significant variable impacting the resilience and the performance of humanitarian SCs (Dubey *et al.*, 2022).

3.3.3.2 Explainability and AI (XAI)

Explaining is an ongoing process in which humans are motivated to understand goals, intent, context awareness, task limitations, and the basics of system analysis to see if a system can be trusted. However, the explainability of an AI-type digital device is its ability to support an explanation process by providing the means for users to understand the models, and the data they used, during their implementation for a specific use.

The XAI concept is the ability to understand overall strengths and weaknesses, predict future behavior, and, finally, convey how to correct the system's mistakes.

The complex nature of modern learning systems and the lack of interpretability and explainability of these systems make decision-making complex, especially in high-stakes contexts; hence, the need to integrate the notion of explainability into modern learning systems to guarantee an explanation for each result and to ensure the ability of human operators to interpret this result (Rudner et al., 2021).

The end user is a target actor of XAI, which depends on the decisions, recommendations, and guidelines of the system. The user must understand the rationale for the decisions made by the system and trust the system and effectively manage it.

3.4 A method for viable SC

The proposed method aims to study a variety of well-known machine learning metrics and algorithms and ways to improve the delivery of interpretable results. The classifiers can be trained to ascertain whether a SC is still viable in a crisis, particularly regarding the aspect of the presence

or absence of supply delays and then use unknown data to predict whether future supplies will be late or not; in other words, whether there is a risk of late delivery or not.

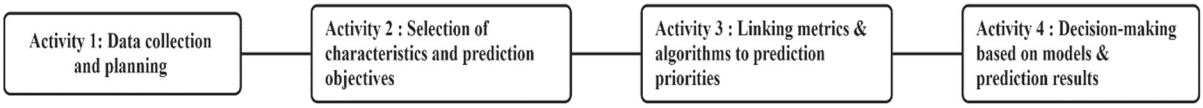


Figure 3.7: Flowchart showing the proposed method

The method proposed in Figure 3.7 is generic and can be a valuable tool to support the management of any emergency or crisis disrupting economic activity, whatever the cause. Each activity is employed as follows:

- *Data collection and planning*: during this phase, all companies have activated working groups and crisis units to manage the emergency at both local and company levels. Executives have asserted that in all situations, the needs of the service business (internal on-site service, branches, and service partners) are considered the same as those of the product business (factories, sales offices, and administrations).
- *Choice of characteristics and prediction aims* cooperation between all parties involved, both inside and outside the company, is required to implement any quick fixes pragmatically. Such operational strategies are implemented to change, to some extent, how services are delivered and, in some cases, to design alternative services.
- *Linking metrics and algorithms to prediction priorities*: at this point, the key questions for business leaders can be summarized as follows: what products and services will be requested on restart? How much of the demand was lost, and what was merely delayed? What adjustments to production ability will be needed to cope with peaks in demand? What abilities should be developed to cope with the complexity of the business environment?
- *Decision-making based on models and prediction results*: this concerns the creation of more resourceful organizations ready to evolve to avoid failure. In addition to consolidating or adapting current measures, thought must go into creating new practices, reconsidering established mental models (e.g., product-centric business logic), changing configurations, and strengthening network relationships.

The variables selected to train the models included vaccine delivery volumes, transportation lead times, safety stock levels, and logistical distances. These variables were chosen because they directly reflect the key indicators of SCR, such as continuity of flows and availability of

essential products. Their inclusion ensures that the models capture both demand-side and supply-side disruptions observed during the crisis.

3.4.1 Machine learning metrics and algorithms

The SC's environment is particularly suited to using these techniques because it is characterized by a large amount of data that can be read and processed to automate and simplify processes, reduce costs, and make predictions for the future. Modern learning systems are applied in different fields (banking, human health or autonomous driving, etc.) for automated decision-making (Kumar *et al.*, 2022).

Exploiting specific data allows the shortcomings of the process to be highlighted and the probability of returns and delays to be predicted using machine learning models. AI is helping to identify the essential parameters to fill the gaps and end inefficiencies in the SC process. A machine learning (ML)-based method enables a prognostic approach rather than a traditional one in an increasingly volatile and complex context, such as the COVID-19 pandemic crisis. Based on specific challenges and constraints such as those met during the pandemic, algorithms can be customized by:

1. Collecting
2. Cleaning and combining data from all relevant sources
3. Sorting relevant information affecting the resilience and viability of a SC

Data collection is relevant; processing and analyzing these data is even more relevant to ensure the SC's stability, robustness, resilience, and viability. It is a question of ensuring a correlation between the factors that have a maximum impact on transactional data to predict a disruptive event, anticipate it, and plan to get out of the crisis. The major challenge today is ensuring accuracy, so using explainable machines is a good way to provide explainable results without conscious or unconscious bias.

Interpretable learning systems are proving to be valuable at considering causal factors that influence demand and forecasting post-pandemic demand for new products, including the causal factors that have driven recent sales the most, which is an area ML can be applied. Interpretability in ML is crucial for high-stakes decisions.

In addition, the medical emergency observed during the COVID-19 pandemic crisis has helped to highlight the importance of SCRE to deal with unlikely and unprecedented events, such as the race to prevent and reduce infections, including through mass vaccination against the virus.

In the context of supervised learning, the data are labeled, and each input observation is associated with an output variable. The aim of the algorithm is, therefore, to learn to associate observations and labels from this data.

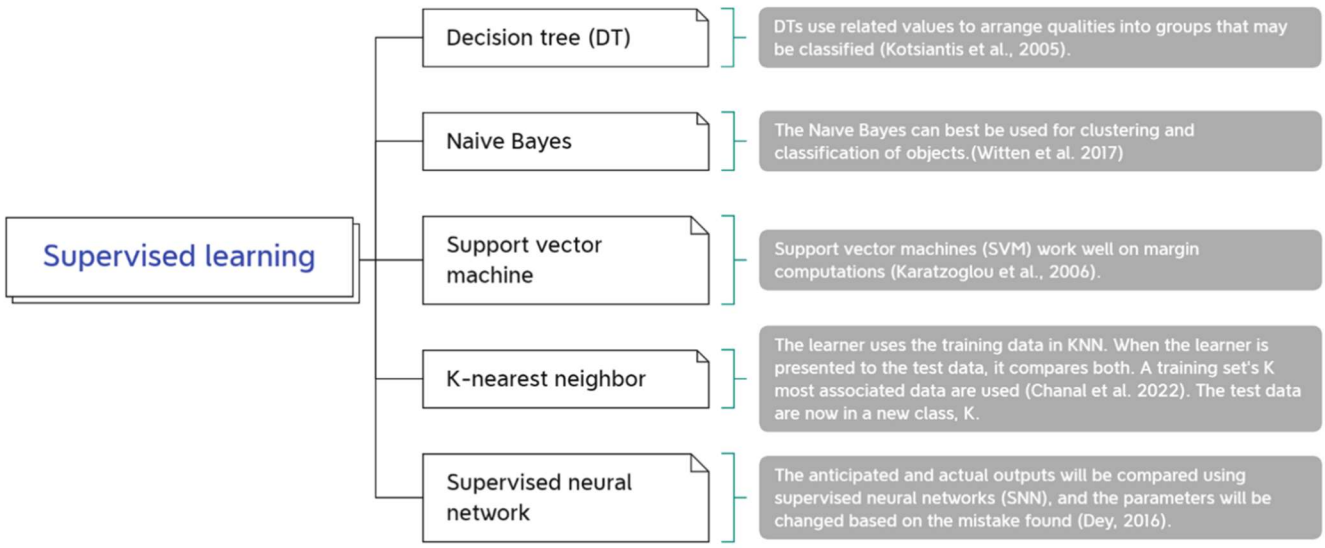


Figure 3.8: Supervised machine learning algorithms (Chanal et al., 2022; Dey, 2016; Gupta et al., 2020; Ikonomakis et al., 2005; Karatzoglou et al., 2006; Witten et al., 2017)

For unsupervised learning, the data are not labeled, so the algorithm aims to identify common characteristics within the data and, thus, discover underlying structures.

Figure 3.9: Unsupervised machine learning algorithms (Dey, 2016; Koh et al., 2012; Shalev-Shwartz et al., 2011)

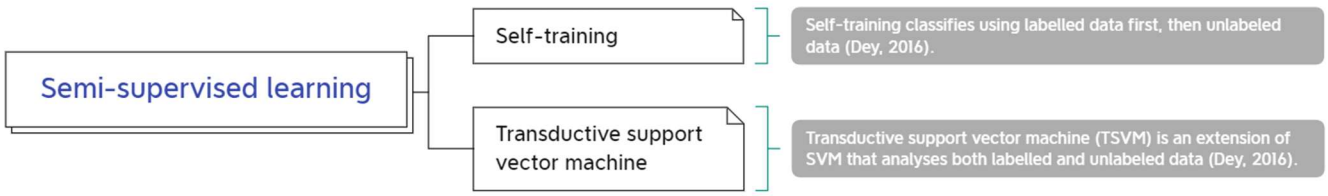


Figure 3.10: Semi-supervised machine learning algorithms (Dey, 2016)

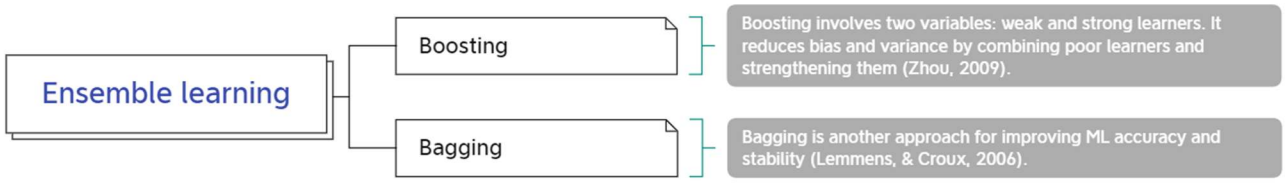


Figure 3.11: Ensemble learning algorithms (Shalev-Shwartz et al., 2011; Zhou 2009)

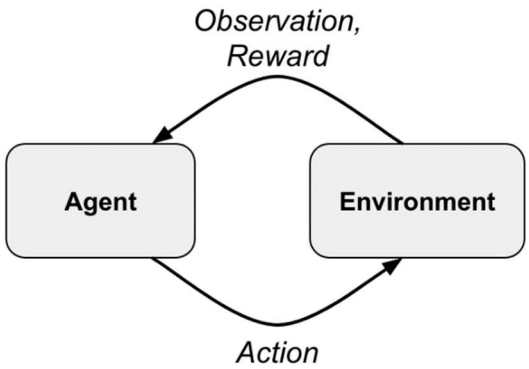


Figure 3.12: Reinforcement learning

Reinforcement learning is an area of ML which stands as one of the three ML paradigms, alongside supervised and unsupervised learning. It refers to the set of methods that allow an agent to take suitable action to maximize reward in a particular situation.

According to (Valluri et al., 2009), reinforcement learning has proven to be a beneficial technique in multi-stage supply chains that involve numerous learning agents. Due to the independent agents' capacity to acquire necessary skills to coordinate their movements, the occurrence of such an event is highly unlikely.

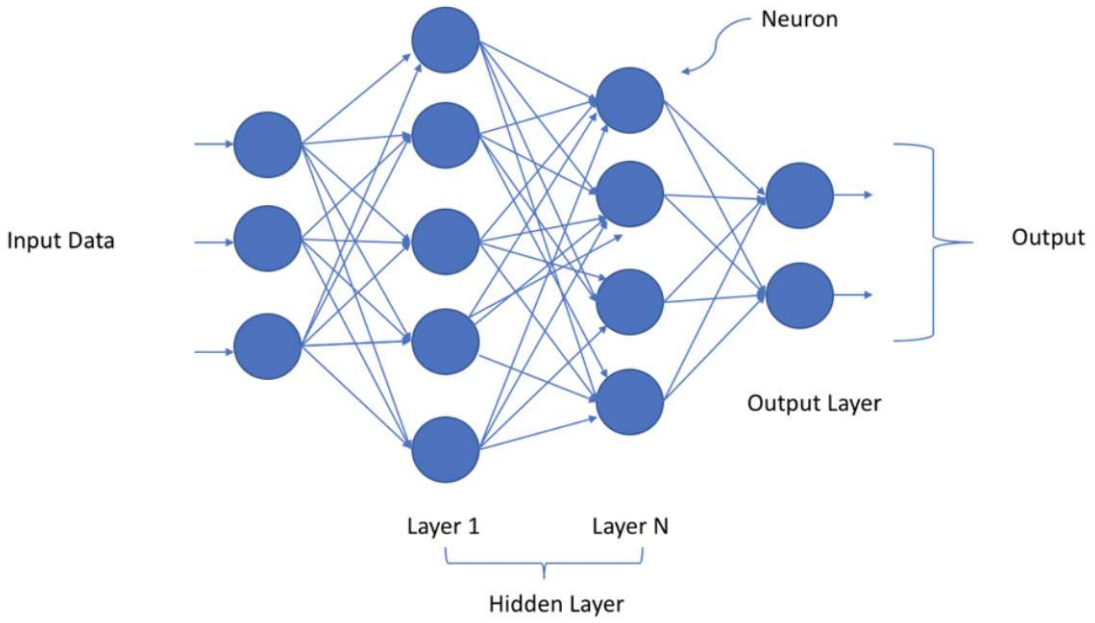


Figure 3.13: Deep learning

Deep Learning is a technique that constructs artificial by taking metadata as an input and using it through several non-linear layers to compute the output classification (Kamsu-Foguem et al., 2018).

This learning technique is a tool for processing massive quantities of data related to the performance evolution of the machine. Deep learning algorithms are stacked in a hierarchy of increasing complexity and abstraction.

With the increase of data, the machine becomes more adept at recognizing hidden patterns and, consequently, learning from them after they have been processed. Thus, it can perform, from the raw data, feature extraction and abstraction automatically, with little or no human input.

Deep learning has produced many promising results for various situations, such as solving problems in many domains of science, business, and government (lecun et al., 2015).

3.5 How technologies of AI such as ML are used in Healthcare SCs

The scarcity of critical medical supplies caused by the COVID-19 pandemic led to considerable procurement challenges in the healthcare SC. The ability to meet those challenges and implement effective strategies supplying details on equipment, facilities, and resources needed for the recovery of operations for sustainability during the crisis was a real asset for organizations.

A crisis is characterized by its rapid evolution and proportions, and it is likely to call into question an organization's ability to cope with the situation: more precisely, its ability to mitigate the risks of shortages of raw materials.

Uncertainty is inherently high and the mitigation, preparation and management of such disruptions are more critical in healthcare SCs compared to other industries. Considering the direct implications for human lives, health SC systems must be designed to ensure and reliably deliver essential health commodities such as medicines, vaccines and personal protective equipment during infectious disease outbreaks (Spieske *et al.*, 2022).

During this crisis, we saw a change in basic assumptions. Indeed, current needs were no longer the same and additional needs were more important, qualitatively, and quantitatively. The environment became increasingly vulnerable following periods of quarantine and containment. Several misbalances were experienced in supply and demand due to drops in demand, longer lead times and the unavailability of supplies due to facility closures.

The anticipatory logic in supply management had to be accentuated to predict the current needs

of patients and to detect, as early as possible, the most essential needs to organize an adapted response.

For example, by utilizing ML and deep learning models to identify vaccine-hesitant messages, health campaigns and supply chain stakeholders were able to gain insights into the sentiments and concerns expressed by individuals. This information could be used to develop targeted strategies to address hesitancy, provide accurate information, and improve vaccine acceptance. Ultimately, addressing vaccine hesitancy contributed to a more resilient and efficient COVID-19 vaccine SC by providing adequate and timely distribution of vaccines to the population (Nyawa et al., 2022).

3.5.1 Analysis and synthesis of the application case

During the COVID-19 crisis, we noticed difficulties suppliers were having in finding raw materials to increase their production capacity and be able to meet the ever-increasing global demand. This created upstream stock-outs in the supply chain in some countries, which disrupted their vaccination schedules. Therefore, it was fundamental that challenges to the COVID-19 vaccine supply chain were identified and prioritized to pave the way out of the pandemic (Liu et al., 2022).

To achieve sustainable cities and communities, it is imperative to invest in learning systems that can be interpreted and explained in vaccine supply chains, enabling correct demand forecasting, the prediction of challenges or disruptions that may interrupt the SC, and surveillance of the vaccinated population to design successful vaccination campaigns. Because of the independence of inputs such as lipids, adjuvants, excipients, vials and so on, required for the production of vaccines, only a few countries had all the resources necessary for the production of a vaccine (Alam *et al.*, 2021).

The vaccine SC involved the production of antigens and inputs from different countries to be transported by air to vaccine production plants. This chain was particularly affected by air cargo and other transportation disruptions.

Because the vulnerability of vaccine supply long pre-dated the pandemic, the need for solutions that extended beyond pandemic response capacity was emphasized (Gilani et al., 2022). Safely delivering COVID-19 vaccines was the most complex mission of the century for the global supply chain network. By considering factors like immunity ratio, vaccines, and medicines, one notable example is the the Susceptible-Immune-Infected-Recovered (SIRM) model stands out

as suitable for predicting Covid-19 behavior (Al Qundus *et al.*, 2023).

In this chapter, we reviewed datasets corresponding to the deliveries made and the doses of COVID-19 vaccine forecasted in metropolitan France, specifically in the Auvergne-Rhône-Alpes (ARA) region, by vaccine suppliers (Pfizer-BioNTech, Moderna, AstraZeneca) (Gouv, 2022) from January 2021 to December 2021.

The recipients of the Pfizer-Biontech, Moderna, and Astrazeneca shipments were:

- Depository logistics platforms, subcontracted by Santé publique France, which centralized several shipments to optimize transport flows to downstream recipients (pharmacies, elderly dependent care accommodation (homes)) (EHPAD).
- Health establishments known as "hubs", such as general hospitals (CH) and university hospitals (CHU).

Specifically, these deliveries were distinguished according to the supply flow: Pfizer A flow, Pfizer B flow, Pfizer Pediatric flow, Moderna flow, Astrazeneca flow and Janssen flow.

- **Pfizer A**

Following the recommendations of the High Authority of Health, the government chose to vaccinate people most at risk as a priority. Thus, the logistics scheme was built around the imperative to vaccinate the residents of nursing homes as a priority.

In addition, the storage conditions of the Pfizer vaccine dictated part of the logistics scheme. As a reminder, this vaccine had to be stored at -80°C. Once thawed, the bottle had to be stored between 2°C and 8°C and used within five days. The dose produced in Pfizer factories was transported to one of France's five public health storage platforms, allowing storage of the vaccine at -80°C.

- **Pfizer B**

The Pfizer B-Stream Flow B served about a hundred health facilities to supply residential facilities for dependent seniors (nursing homes) and vaccination centers. Indeed, more than 1,000 such centers were opened so that people over seventy-five years old could be vaccinated, as well as health and medical staff over fifty years old and people with comorbidities. Thus, the logistics were based on health facilities with freezers allowing storage at -80°C which were provided by the state.

- **Pfizer Pediatric Feed**

Deliveries of the pediatric Pfizer vaccine began at the end of December 2021. They were

distributed to the same health facilities as the deliveries of flow B. Pfizer Pediatric deliveries since the March 4, 2021, update have been included in the data in this chapter.

- **Moderna Flow**

The Moderna vaccine had different storage conditions; it needed to be stored at -20°C. Once thawed, it needed to be stored at between 2°C and 8°C and had to be used within 30 days. Due to the small number of Moderna doses received in January 2021, these vaccines were delivered as a priority in January to health facilities located in regions with a high epidemic circulation. The distribution of the Moderna vaccine was executed in a comparatively restricted array of locations in contrast to the Pfizer vaccine. Specifically, it was disseminated to two to seven health facilities in each region, where specialized freezers were available to permit storage at -20°C. Dose allocation was conducted at the regional grid in proportion to the target population of vaccination.

The distribution at the departmental level was the responsibility of local actors (the Regional Health Agency). The logistics relied on a public health subcontractor in France and health facilities. Doses stored in pivotal facilities were delivered to vaccination centers. A national stock was also kept according to the weeks in the platform of the subcontractor of Public Health France. The conversion rate between common dispensing units - vials (UCD) and doses was x10.

- **Astrazeneca flow**

The first Astrazeneca deliveries were to healthcare workers. 107 vaccination centers covered the provision of doses for health professionals. Deliveries to general practitioners (family doctors) were distributed to more than 7,000 pharmacies before the vaccination opened on 25 February 2021. The distribution was made based on requests collected by pharmacies. The last Astrazeneca deliveries took place in June 2021.

- **Janssen Flow**

The Janssen vaccine's first deliveries took place in France on 12 April 2021. The vials were distributed to pharmacies for distribution between the different effectors in the city (pharmacies and health professionals). This vaccine required only one injection. The conversion rate between UCD and doses was x5. The last Janssen deliveries took place in September 2021.

3.6 Application case in France: Deliveries of COVID-19 vaccine in the Ain department - ARA Region

The data on COVID-19 vaccine deliveries in the vaccination centers and places in the Ain department used in this chapter were taken from those held by the Ministry of Solidarity and Health of France, updated on May 2, 2022 - Open License version 2.0 and were analyzed using Python.

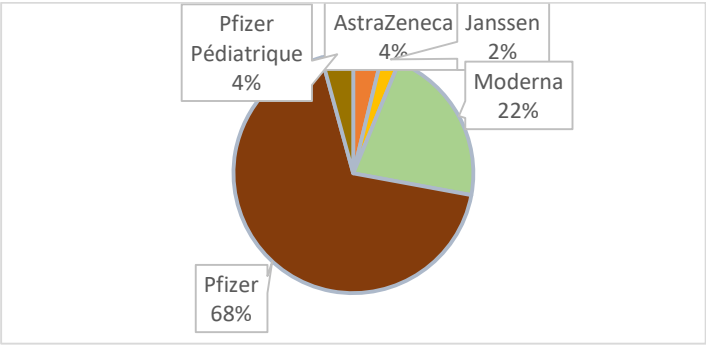


Figure 3.14: This shows the national deliveries in UCD (common dispensing units - vials) from January 1 to December 31, 2021, in France.

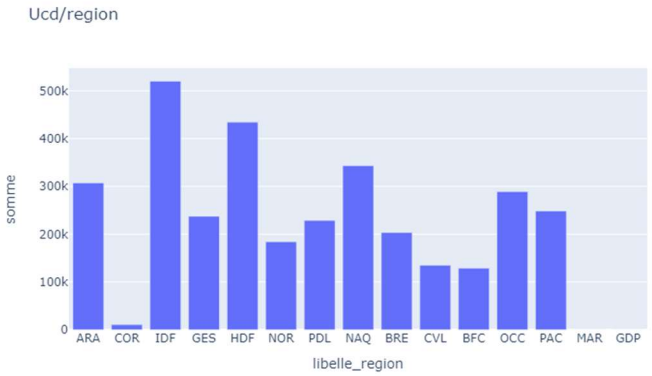


Figure 3.15: The national deliveries in UCD Astrazeneca in the ARA region, ranked fourth in terms of quantities delivered.

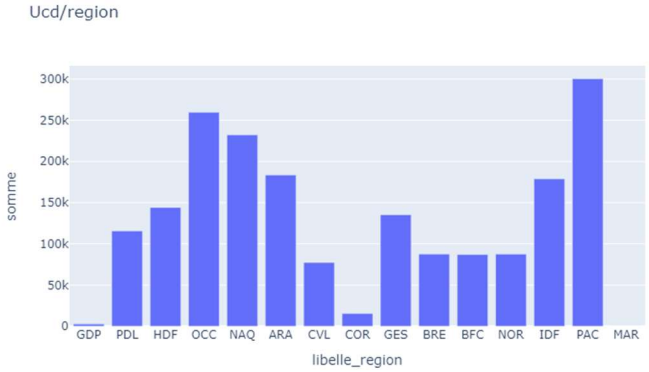


Figure 3.16: The national deliveries in UCD Janssen in the ARA region, ranked fourth in terms of quantities delivered.

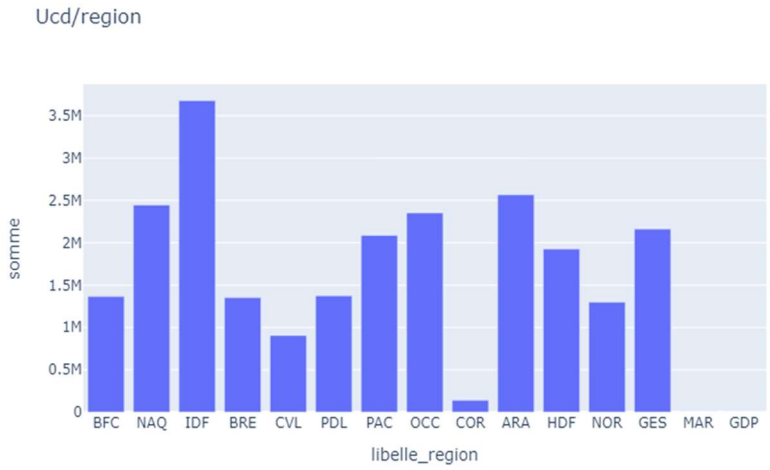


Figure 3.17: The national deliveries in UCD Moderna in the ARA region, ranked second in terms of deliveries.

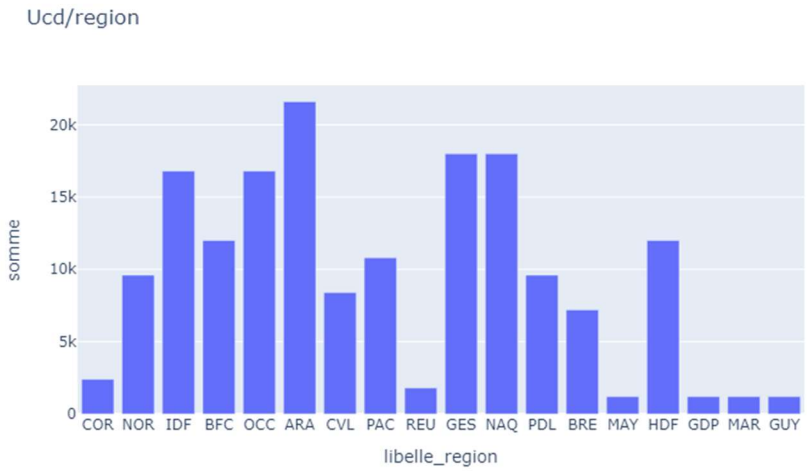


Figure 3.18: The national deliveries in UCD Pfizer Pediatric in the ARA region, ranked first in terms of vaccine deliveries.

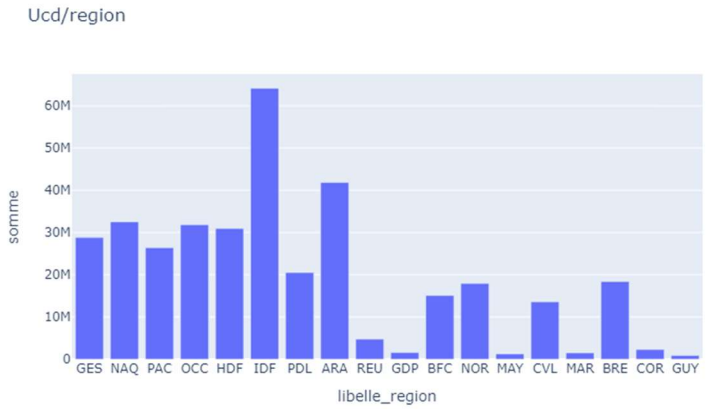


Figure 3.19: The national deliveries in UCD Pfizer in the ARA region ranked second in terms of vaccine deliveries.

This diagram illustrates the weekly incidence rate, which represents the number of new patients over a given period concerning a given population by region. With a positivity rate of 24% recorded on October 5, 2020, and 37% on January 10, 2022, the ARA region was one of the French regions to have been particularly strongly affected by the coronavirus pandemic.

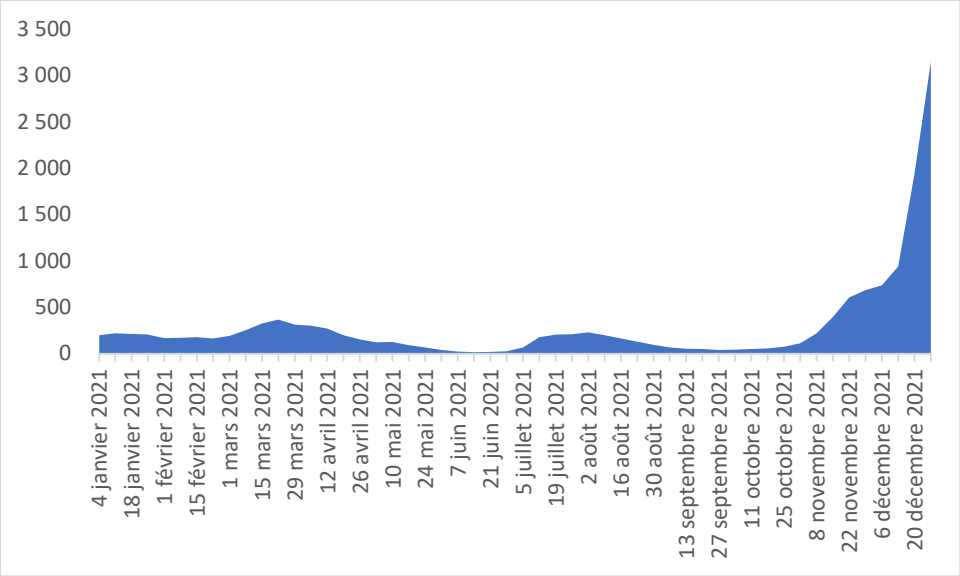


Figure 3.20: The COVID-19 incidence rate in the ARA region 1st January 2021 and 31st December 2021.

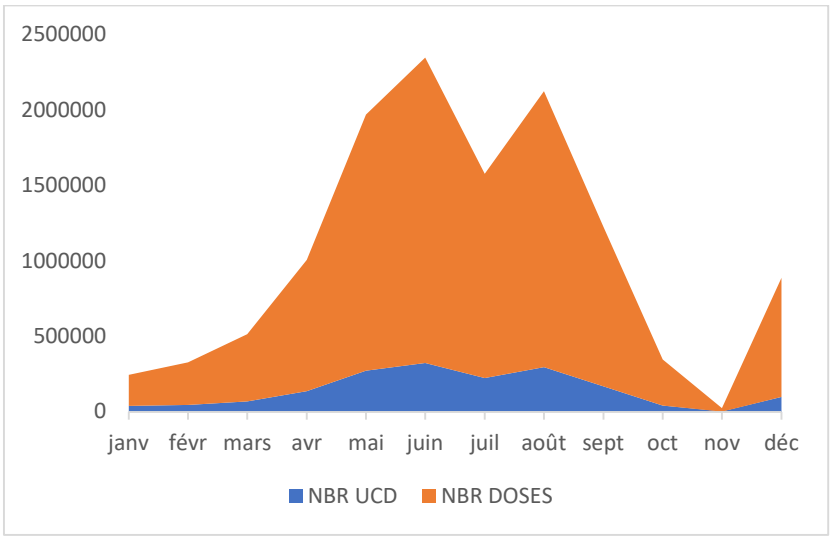


Figure 3.21: National deliveries made and forecasts per month, in UCD (common dispensing units - vials) and doses, in the ARA region. (Pfizer doses were counted based on a UCD/dose conversion rate of x5 before January 18 and x6 thereafter).

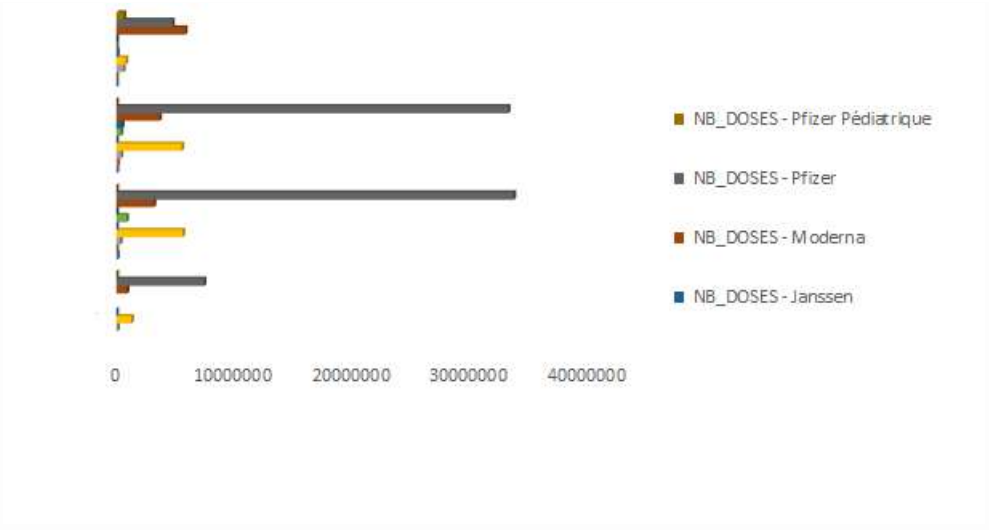


Figure 3.22: The delivery flows of vaccine doses by type of vaccine in the Ain Department.

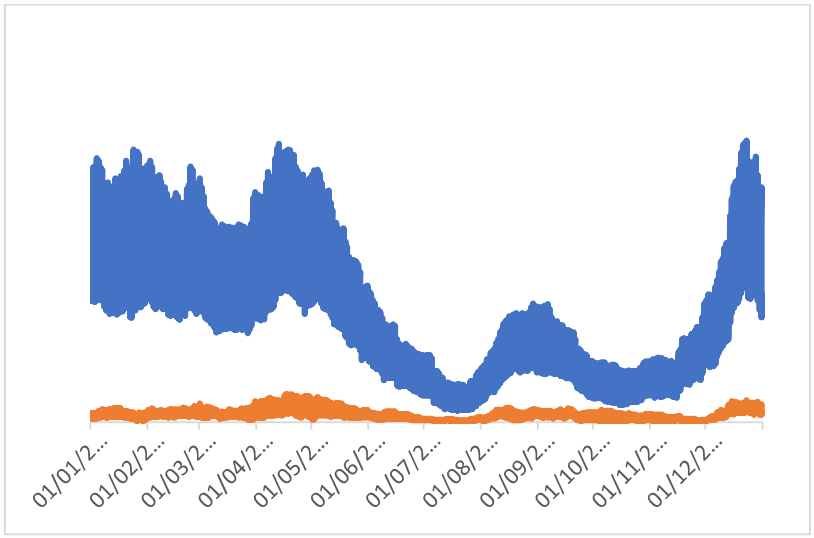


Figure 3.23: The COVID-19 hospitalization incidence in the ARA region between the 1st of January 2021 and the 31st of December 2021.

According to Figure 3.21 and Figure 3.23, the rhythm of deliveries increased considerably in correlation with the increase in the number of hospitalizations. Indeed, vaccine delivery flows decreased between June 2021 and July 2022 (because of a low hospitalization rate in the ARA region) enough to generate an increase in the number of daily injections.

Therefore, with the increase in COVID-19 patient hospitalization in the ARA region, supply chains significantly impacted vaccine coverage. Particularly, resilient SCs enabled the delivery of live-saving vaccines to every person when needed, no matter where they were. The challenges were the inconsistent availability of high-quality vaccines and the limited reach of the vaccine supply chains to underserved populations which threatened access, immunization coverage, and equity outcomes, and put vaccine investments at risk.

It should be noted that, due to the lack of sufficient deliveries because of the serial delays that affected the vaccination campaign with Astrazeneca and Janssen, deliveries to the ARA region also experienced disruptions, as shown in Figure 3. 23.

3.7 Results

3.7.1 Supervised learning

Supervised learning consists of showing the machine examples and asking it to find an association that connects inputs (x) to outputs (y) (Russell Reed, 1999). In our case, the target variable is the vaccination rate against COVID-19, while the features represent the logistical and operational factors influencing this outcome.

Through a learning algorithm, the machine seeks to minimize the cost function by iteratively modifying parameters, using gradient descent as a typical optimization method. The accuracy of AI systems depends on the quality of the collected data and on the way the algorithms are designed and implemented, which may raise ethical concerns in sensitive domains such as healthcare.

Artificial neural networks (ANNs) are a widely used supervised learning method for solving complex problems. Inspired by biological neurons, these networks are composed of input, hidden, and output layers. In this chapter, several hidden layers and parameters were assumed to capture the complexity of vaccine distribution dynamics.

To predict the vaccination rate of a population or the delivery rate of vaccine doses, the ANN required multiple input factors, such as the number of available vaccines, the locations of storage areas, the number of suppliers, and the modes of transport employed. Based on these data, the models learned to correlate vaccine availability, delivery capacity, and vaccination uptake within target groups, in order to assess scenarios with unknown outcomes (Baryannis et al., 2019).

We assume for the input layer of the neural network the following input variables:

Input type	Inputs
Demographics	Population, sex, age groups
Vaccine manufacturers	Pfizer-Biontech, Moderna Tx, Oxford-Astrazeneca, Janssen (Johnson & Johnson)
Quantities of vaccines ordered	Number of vaccines required by vaccine type
Target geographical areas	Regions, departments

Number of storage areas	Number of storage spaces with adequate facilities for assembling, packaging, receiving, and shipping doses of COVID-19 vaccines
Modes of transport	Air Transport Transport by refrigerated trucks Transport between airports and domestic warehouses

Table 3.2: Illustration of the variables to be used as input data in the artificial neural network.

The following data can impact the expected result: the vaccination rate against COVID-19 using as intermediate parameters the number of deliveries per region, the demand for vaccine quantities by region, etc.

For example, based on the quantities of COVID-19 vaccines delivered by region (cluster), we can define a correlation between the number of people vaccinated per region and the geographical areas with similar vaccination rates.

3.7.2 Unsupervised learning

This learning method comprises providing only x data and analyzing the structure of this data to learn how to perform certain tasks.

By correlating the number of people to be vaccinated by age and sex, AI can learn, through a set of supervised classification methods, to assess the number of people vaccinated by age and sex category.

The clustering method helps to classify data by grouping it only according to its similarity and by taking into consideration characteristics of the input data to predict the COVID-19 vaccination rate and the delivery rate of vaccines in line with demand.

The following variables can be collected and analyzed: demographic data (population density, age by category), number of vaccines required, number of storage areas, number of vaccine suppliers, storage conditions, and modes of transport used to transport vaccines to immunization centers.

A cluster update is performed by recalculating the cluster centroid; the algorithm runs repeatedly until convergence is achieved.

By analyzing the structure of the data, the machine learns how to simplify this structure while maintaining the main information and, therefore, projecting our data as best as possible into smaller spaces.

3.7.3 Semi-supervised learning

Semi-supervised learning falls in between supervised and unsupervised learning. The training dataset comprises a small amount of labeled data, such as the number of required vaccine doses, number of people per age, sex, etc., and a large amount of unlabeled data.

Type of learning system	Inputs	Outputs
Supervised learning	Demographic information: population density, age distribution by category.	Predicting the vaccination coverage rate in different demographic segments (e.g., based on age categories, population density)
	Vaccine-related inputs: number of vaccines required for the target population.	Estimating the number of vaccines required for a specific population based on demographic information and storage conditions
	Supply chain inputs: number of storage areas, number of vaccine suppliers.	Forecasting the expected delivery time for vaccines considering transportation modes and conditions.
	Storage conditions: factors such as temperature requirements and other storage specifications.	Predicting the optimal allocation of vaccines across different storage areas or vaccine suppliers based on demand and supply factors.
	Modes of transport: information about the transportation methods used for vaccine delivery.	
Unsupervised learning	Number of people to be vaccinated: the total population targeted for vaccination.	Segmenting the population based on vaccination behavior and demographics to tailor targeted vaccination campaigns.
		Determining geographical areas with similar vaccination rates and identifying potential gaps in coverage for specific groups.
	Demographic inputs: age, sex, and target regions of the population.	Discovering hidden patterns or relationships in the data to understand the factors influencing vaccination rates.
	Additional variables: factors that may influence vaccination rates, such as socioeconomic status, previous vaccination history, or healthcare access indicators.	Identifying clusters or groups of people with similar vaccination patterns based on age, sex, and target regions.
Semi-supervised learning	Labeled data: demographic information, number of people to be vaccinated, number of vaccines required, and quantity of vaccines ordered.	Predicting the rate of vaccine adherence based on demographic factors and the number of people vaccinated.
		Estimating the impact of vaccination campaigns on different population segments using a combination of labelled and unlabeled data.
		Predicting the future demand for vaccines based on historical data and available labeled information.
	Unlabeled data: unknown or unlabeled data that can contribute to the learning process, such as additional demographic information or vaccination-related data.	Assessing the effectiveness of different strategies for vaccine distribution and resource allocation by combining labeled and unlabeled data.

Table 3.3: Illustration of inputs and outputs according to the type of learning system in our study

Understanding the planning of COVID-19 vaccine supply chains requires acknowledging the complexity of the process. This complexity can be mitigated through the analysis of data using a learning system. The COVID-19 vaccine strategy comprises three primary steps: operations and planning, the movement of syringes, and the inoculation of the patient. Each of these steps is directly connected to the local context of an SC.

The use of learning systems can facilitate the mapping of end-to-end delivery, enable planners to predict optimization based on supply chain fluctuations, and provide real-time updates. Additionally, it can operate a transparent and secure system that could help healthcare providers adjust resources on the ground. These systems are designed to leverage the historical records of demographic data, the number of vaccinated people, and the number of people to be vaccinated in order to predict COVID-19 vaccine delivery SC planning. One of the vital criteria for the equitable distribution of vaccines is predicting the geographic distribution of the active virus at the time of vaccination.

The need for a centralized data-driven prioritization strategy results in greater complexity for logistics actors who must face last-minute changes to demand and routing. They will potentially have to manage the returns of the remaining doses. Collecting data on infection rates relative to human behaviors can help governments and businesses dynamically adjust the need for COVID supplies and safety protocols, such as distancing, air and sea traffic restrictions, and consumption behavior related to specific products or drugs.

It is highly improbable that an AI could analyze real-time data inputs, like the number of vaccines required, storage location, vaccine suppliers, storage conditions, and transportation methods, to identify priority locations based on their distance from the distribution center and each other for optimal vaccine delivery per shipment. The use of AI technologies ensures the efficient and safe delivery of COVD-19 vaccines to their various destinations and can predict shortages.

Unsupervised learning can be accomplished through clustering, which groups events into clusters and simplifies the analysis of COVID-19 vaccine supply chains. This approach can be used for statistical data mining and analysis. A clustering model can be utilized to categorize patients into groups according to population density, sex criteria, and other related factors.

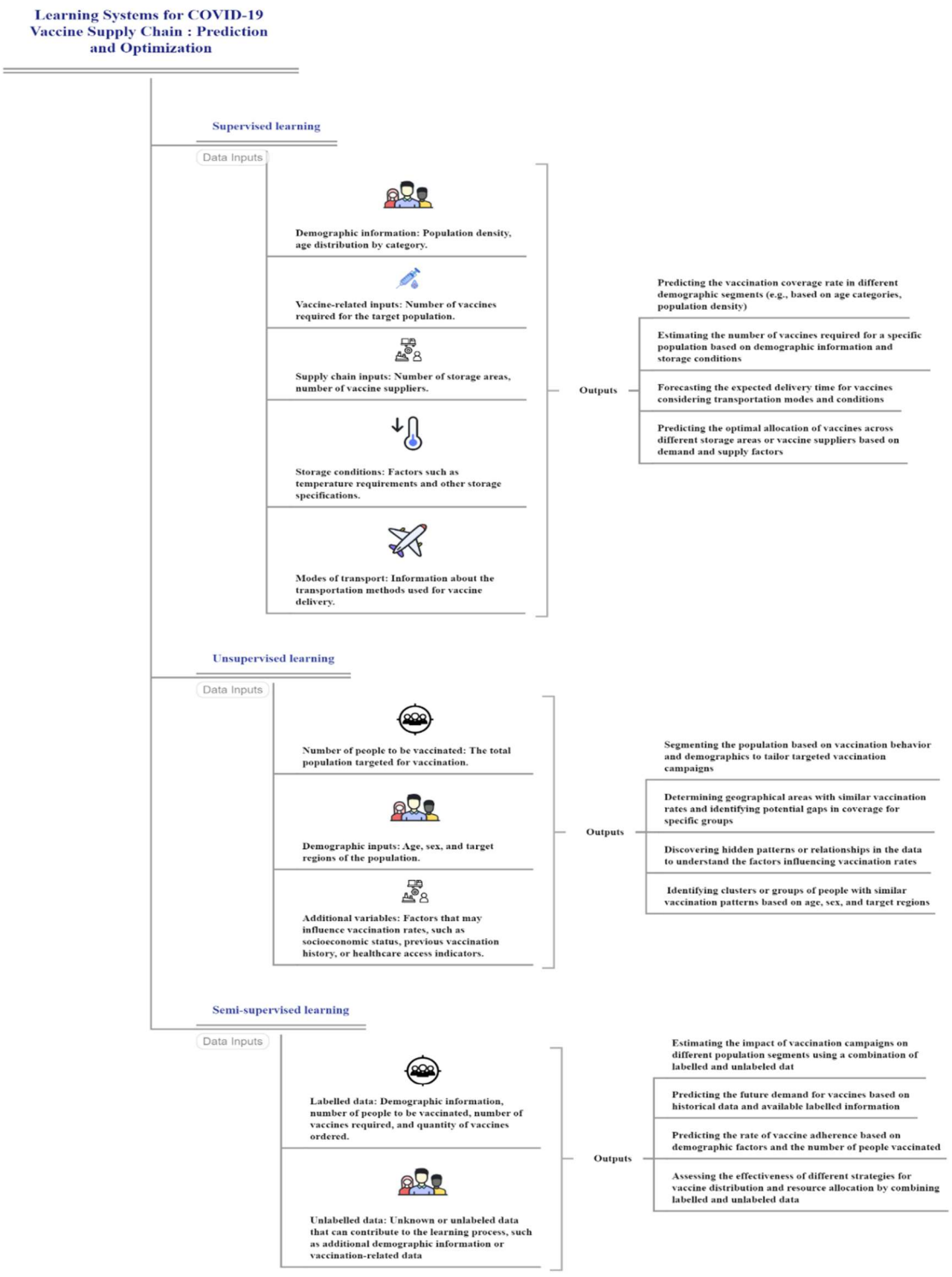


Figure 3.24: An illustration of the application of learning systems to predict a resilient COVID-19 vaccine SC

Finally, we can significantly reduce the number of deaths and cases and increase the safety of the world population by ensuring that large groups of people can get the vaccine at once in a way that is both cost-effective and quick. In this regard, some influential parameters are difficult to measure, analyze and predict using AI, namely lockdowns, and sea and air transportation suspensions. This may lead to considerable revenue loss or economic blockades. There may also be a need for the compliance of public opinion or certain choices regarding vaccination being taken, such as the obligation of the vaccine pass. This has helped encourage people who were reluctant to get vaccinated and, thus, ensured wider vaccination coverage.

3.7.4 Contribution of the case study data in viability and resilience concepts

According to WHO recommendations, a country's roll-out of a COVID-19 vaccination campaign requires meticulous preparation in terms of the vaccine supply chain to ensure the quality, integrity, and safety of the vaccines and related products involved.

In this case, for the successful deployment of COVID-19 vaccines, the rigorous management of supply chain information was achieved by:

- The control of cold chain performance and capacity to ensure the availability and security of the storage space at target sites.
- The control of stock distribution and disposal to ensure that vaccines were distributed on each site in the required quantity and that they were effectively used.
- Ensuring that the supply chain had sufficient capacity to deliver COVID-19 and routine vaccines (vehicles, insulated boxes, vaccine holders) promptly.

Therefore, when considering digitalization techniques, they should include storage/transport requirements, GS1 standards and barcodes (GS1), distribution channels and supply chains, supply volumes, and target population to ensure SC resilience and viability.

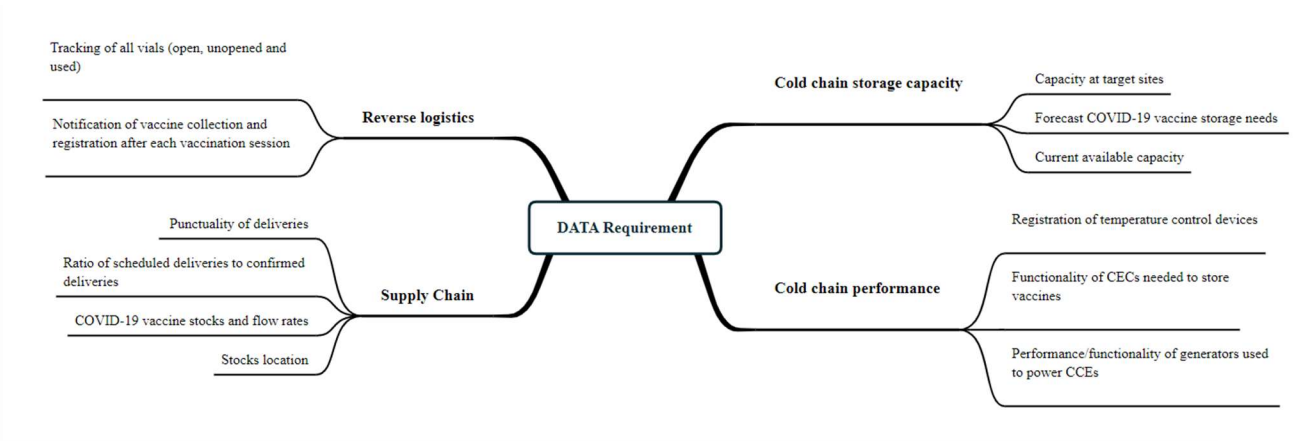


Figure 3.25: Summary of the areas in which the data collected and recorded will need to be analyzed.

WHO strategic guidance for managing the supply and logistics of COVID-19 vaccines recommended that to control and anticipate these vulnerabilities, the risk factors to be targeted and monitored should be identified to better predict and, consequently, optimize the SC and guarantee its viability.

3.8 Discussion

3.8.1 Strategic data management solutions for a viable COVID-19 vaccine SC

The discussion section provides an interpretation of the findings and their implications for theory and practice. It highlights the significance of addressing the challenges faced by COVID-19 supply chains and the importance of implementing strategic data management solutions. By leveraging learning systems, SC's operations can be analyzed and adjusted to ensure sustainability in the face of disruptions caused by high demand and limited vaccine quantities.

Strategic data management solutions enable the collection and transmission of critical information related to transportation, inventory, and human resources. This includes information on transportation details, networks, available means of transportation, and the location and condition of transport vehicles. Real-time data on delays, necessary resources, fuel suppliers, and repair sites are also accessible.

To protect against falsification, fraud, and vaccine diversion, it is crucial to establish viable systems based on GS1 standards. In the case of the digitalization of the COVID-19 vaccine supply chains, the implementation of QR codes was one such solution. QR codes enable the traceability of vaccine movements, the real-time monitoring of vaccine stocks, the identification of pre-emption dates, and the tracking of batch numbers. These measures helped safeguard the vaccine SC from disruption which would hinder the vaccination campaigns.

Digitalization measures, such as barcode-based tracking and the tracing of vaccines, played a vital role in enhancing supply chain viability. They enabled the early detection of upstream delays caused by various factors and facilitated appropriate solutions. Furthermore, these measures assisted in the detection of fraudulent activities that may have distorted accurate stock-level assessments. They also supported the recall of specific vaccine batches in response to adverse post-vaccine manifestations, allowing for adjustments in vaccine consumption, stock levels, and overall supply chain optimization.

AI can support the work of pharmacovigilance experts during crises like the COVID-19 pandemic. AI systems can process and analyze COVID-19 vaccine side-effects reports, leading to better stock levels and demand prediction. This information contributes to informed adjustments in vaccination strategies.

3.8.2 Case in point: Uncertainties about inventory volumes and actual deliveries caused by human error

The COVID-19 pandemic has presented unprecedented challenges to healthcare supply chains, necessitating a focus on resilience and viability. Interpretable and explainable learning systems play a crucial role in managing SC risks effectively. They enable proactive decision-making, predict logistics activities, and anticipate necessary supplies for managing patient influx in hospital settings. These systems can specifically target sensitive products within healthcare chains, contributing to effective risk management (Abdulsalam *et al.*, 2015; Chakraborty, 2019; Chatterjee *et al.*, 2021).

During times of crisis, the availability of human and physical resources is vital across all stages of supply chains. This includes the administration of COVID-19 vaccines, which represents the SC's last and most complex stage (Singh et al., 2022). However, the human factor in vaccine administration can introduce uncertainties and disruption due to human error or negligence.

AI technologies become indispensable to addressing these challenges and ensuring the COVID-19 vaccine SCV. By leveraging AI, SC's managers can optimize the allocation of resources, monitor real-time updates, and predict SC's fluctuations. This enables them to ensure the availability of vaccines during disruption and minimize their effect, facilitating a swift recovery (Nagurney, 2021).

The successful implementation of COVID-19 vaccine deployment and vaccination operations relied heavily on the dedicated staff involved, including vaccination teams, supervisors, campaign monitors, and logisticians. These individuals were at risk of being exposed to COVID-19 infection during their work. Prioritizing and maintaining their health and safety throughout the vaccination campaign was of utmost importance.

The deployment of COVID-19 vaccines has brought to light the issue of insufficient qualified medical staff, mainly attributed to increased workload and absences due to illness. This scarcity of staff has led to significant repercussions on the effective delivery of vaccines to their intended recipients. A concerning incident occurred at a vaccination center where caregivers mistakenly administered saline instead of the Pfizer-developed vaccine, resulting in 140 individuals not receiving the intended doses. This error occurred during the preparation of syringes by nurses at the center.

Specifically, during the vaccine preparation process at the aforementioned center, the preparers extracted 1.8 ml of saline from a serum pod using a needle and a 2 ml sampling syringe. This

serum was then injected into the small vial of the Comirnaty vaccine for dilution. The Pfizer-biontech vial contained 2.25 ml of solution, equivalent to 7.5 doses. The liquid was subsequently distributed into individual injection syringes, with 0.3 ml per syringe, to be administered by the vaccinators. Fortunately, the injected product, a saltwater solution, posed no health risks to the patients as it is commonly used for wound cleaning and as a diluent during injections. This human error was identified retrospectively and occurred during the syringe preparation stage by a nurse.

Such incidents exemplify the potential hazards that can introduce uncertainties in COVID-19 vaccine stocks and human resources. It is imperative to strengthen protocols to ensure safety, quality, continuity, and vaccine traceability. This entails prioritizing measures that promote competence, and the availability of qualified staff, the effective management of workload challenges, the prevention of errors, and the addressing of absences due to illness. The risk of human errors and disruptions in vaccine delivery can be minimized through appropriate training, clear protocols, and effective supervision.

3.8.3 Limitations of the Study and Future Research Directions

In terms of research limitations and future studies, certain ethical considerations must be considered when using AI systems, such as:

- ***Ethical Considerations:*** The use of AI systems raises ethical questions, particularly regarding privacy, bias, and the impact on public health. Future research should address these ethical concerns and develop frameworks for responsible AI implementation in healthcare supply chains.
- ***Data Quality and Availability:*** The accuracy of AI systems heavily relies on the quantity and quality of collected data. Future studies should focus on improving data collection processes and ensuring data accuracy to enhance the reliability and effectiveness of AI algorithms.
- ***Social and Political Factors:*** The study acknowledges that certain influential parameters, such as lockdowns, transportation suspensions, and public opinion, are a challenge to measure and predict using AI. Future research should explore integrating socio-political factors into AI models to provide a more comprehensive analysis and prediction of vaccination rates and SC operations.

3.8.4 Contributions to Practice and Policy

The outcomes of this chapter have significant implications for managers in real-life scenarios. These practical implications include improved vaccine planning, equitable vaccine distribution, and a resilient and efficient SC. We illustrate how the use of artificial neural networks and other learning systems can assist managers in planning the distribution and administration of COVID-19 vaccines by analyzing demographic data, vaccine manufacturers, quantities of vaccines ordered, target geographical areas, number of storage areas, and modes of transport. AI technologies can also prioritize vaccine distribution to needed locations by predicting the geographic distribution of active virus cases and optimizing vaccine delivery per shipment based on distance from distribution centers and between locations. Learning systems can provide real-time updates and predict supply chain fluctuations to make the SC more resilient and viable.

3.8.5 Contributions to Theory

Our research endeavors have resulted in an indispensable contribution to the field of theoretical knowledge by demonstrating the pragmatic implementation of artificial neural networks and other learning systems in the specific context of COVID-19 vaccine planning and distribution. Our contribution is further augmented by the thorough presentation of the effectiveness of supervised, unsupervised, and semi-supervised learning methods, which have provided us with unparalleled insights into their potential for accurately predicting vaccination rates and optimizing supply chain operations. This empirical evidence, which is grounded in a comprehensive and rigorous scientific investigation, strengthens the theoretical foundation of using AI techniques in the supply chain domain.

The integration of data-driven approaches is a crucial aspect that this chapter emphasizes regarding vaccine supply chain management. By employing digitalization techniques, GS1 standards, and barcode solutions, managers can ensure the security, traceability, and integrity of vaccine SCs. This contributes to the overall literature on data-driven approaches and highlights the significance of data management and analysis in SC management.

3.8.6 Conclusion

The global impact of the COVID-19 pandemic has extended beyond public health concerns, causing widespread disruptions in businesses, and revealing vulnerabilities in lead times, order

quantities, network structures, and demand volatility. This crisis has exposed the far-reaching extent of disruption propagation within global SCs, affecting all sectors of the economy and society (Ivanov et al., 2019).

The interrelationships between SCRE and explainable learning systems are highlighted, emphasizing their importance in managing SC risks effectively. The research underscores how SCR and viability should extend beyond addressing single-point failures or disruption and emphasizes the need for consistent assessment and effective monitoring by interpretable learning systems. The importance of employing interpretable and explainable learning systems, supported by impact assessments and benefit-risk analysis, is emphasized. These measures enhance SCR, viability, and the overall sustainability of medical SCs. Finally, the study recognizes the essential role of qualified human resources in ensuring the continuity and security of vaccine deliveries in the final phase of the SC (Alam et al., 2021).

The proposed generic model and vaccine case studies presented in our study exhibit notable distinctions from existing approaches discussed in the literature review.

Our model employs a comprehensive methodology that encompasses a range of factors that can impact COVID-19 vaccination rates, including vaccine quantity, storage facilities, suppliers, and transportation techniques. This approach offers a more holistic perspective of supply chain dynamics which may not be fully captured by current approaches that concentrate on particular aspects. Additionally, our investigation utilizes ML techniques, specifically artificial neural networks, to discern intricate patterns and correlations in the data, which facilitates more precise predictions and scenario evaluations.

In addition, our study recognizes the ethical implications and public health concerns associated with AI applications in the vaccine SC. We highlight the importance of data quality, ethical programming, and addressing potential biases or discrimination. Incorporating these considerations into our model ensures responsible and equitable decision-making, going beyond purely technical aspects.

Furthermore, our research includes specific case studies focusing on vaccine distribution that distinguish it from other studies. By providing practical applications of the generic model in real-world contexts, we showcase its effectiveness and relevance to specific sectors. This practical approach enhances the practicality and applicability of our research.

In summary, our proposed generic model and vaccine case studies differentiate themselves from existing approaches by adopting a comprehensive machine learning-based approach, offering

adaptability and scalability, addressing ethical considerations, and providing practical applications in the field of vaccine distribution.

Chapter 4

Modeling Pharmaceutical Supply Chain Resilience During Arboviral Epidemics: Evidence from Chikungunya and Zika in French Guiana

Abstract

Arboviral epidemics generate demand-side disruptions that are still under-examined in pharmaceutical supply chain resilience research, particularly in geographically constrained health systems. Unlike large-scale production failures, these events may leave upstream supply capacity unchanged while reshaping downstream demand in terms of volume, timing, and therapeutic composition. This chapter develops a simulation-based approach to assess the external pharmaceutical supply chain serving the Andrée Rosemon Hospital Center in French Guiana across a pre-epidemic baseline, successive Chikungunya and Zika epidemic scenarios, and an independent 2017 post-epidemic scenario. Hospital pharmacy consumption records were clinically reviewed, harmonised, and converted into operational demand scenarios by retaining positive and clinically relevant differentials after excluding false-control products, negative differentials, and unsuitable therapeutic categories. Reconstructed demand was temporally allocated using monthly weights derived from official epidemiological curves and introduced into an AnyLogistix discrete-event simulation model. The results show that aggregate demand volume alone does not explain simulated supply chain performance. The Chikungunya scenario introduced the largest reconstructed demand but generated lower backlog than the Zika and 2017 scenarios. Zika produced the lowest expected lead-time service level, while the post-epidemic scenario generated the highest backlog. Temporal normalisation further showed that the 2017 scenario had the strongest backlog pressure relative to its monthly demand base. The study contributes a reproducible protocol for transforming imperfect hospital consumption records into clinically coherent supply chain stress-test scenarios, while distinguishing observed pharmacy activity, reconstructed demand, epidemic timing, and simulated logistics performance.

Keywords: Arboviral Epidemics; Chikungunya; Zika; Pharmaceutical Supply Chain; Resilience; Discrete-event Simulation; AnyLogistix; French Guiana.

4.1 Introduction

Public health emergencies expose weaknesses in the supply chains that connect pharmaceutical production, distribution, and care delivery. The COVID-19 pandemic made these weaknesses visible at a global scale, but the underlying problem is broader. Epidemics can disrupt supply, amplify demand, delay replenishment, and create mismatches between available products and the therapeutic needs of a population (Ivanov, 2020; Queiroz et al., 2020; Schleifenheimer & Ivanov, 2024). Pharmaceutical supply chains are especially sensitive because shortages are not merely commercial failures. They may constrain treatment options, postpone care, and transfer

pressure to other medicines or facilities (Jaberidoost et al., 2013; Miller et al., 2021; Dolgui et al., 2020).

Arboviral epidemics raise a distinct research problem. Chikungunya virus and Zika virus are transmitted mainly by Aedes mosquitoes, and their geographical reach is shaped by mobility, environmental conditions, and the distribution of competent vectors (Leta et al., 2018; Pialoux et al., 2007). Their clinical management is largely symptomatic, but the structure and duration of treatment differ. Zika commonly produces a short and mild symptomatic episode, whereas Chikungunya may cause severe joint pain and persistent musculoskeletal manifestations extending beyond the acute phase (Bertolotti et al., 2020; McCarthy et al., 2022; Pan American Health Organization, 2022). Consequently, the demand signal reaching a hospital pharmacy is not determined by case counts alone. It also depends on symptom severity, care-seeking behaviour, hospitalisation, clinical caution while Dengue is being excluded, and the transition from acute to post-acute pain management.

French Guiana offers a relevant setting for examining this interaction. The territory experienced a Chikungunya epidemic in 2014-2015 followed by a Zika epidemic in 2016. Official surveillance recorded approximately 16,000 clinically evocative Chikungunya cases and about 9,700 clinically evocative Zika cases (Santé publique France, 2015, 2016). At the same time, the territory depends heavily on external pharmaceutical supply and geographically constrained inbound logistics. A demand surge can therefore affect the external chain even when production outside the territory remains uninterrupted.

The empirical challenge is equally important. Hospital pharmacy records are rarely diagnosis-linked, and the extracted product lists may change between years. Direct comparison of annual totals can therefore produce negative differences or apparent increases whose interpretation is uncertain because coding, extraction scope, and clinical activity may all contribute. To preserve traceability, the present study applies clinical filtering and temporal allocation before the reconstructed quantities are used as simulation inputs.

The method treats hospital data as aggregated operational evidence. It identifies clinically relevant medicines, removes a predefined false-control group, excludes negative differentials from the epidemic-associated excess measure, and consolidates the remaining products into scenario-specific therapeutic classes. The hospital-derived positive differentials are not replaced by theoretical prescriptions. Epidemiological data are used only to assess order-of-magnitude plausibility and to distribute the retained phase totals over time. This separation between quantity construction and temporal allocation is central to the study.

The research addresses three questions. RQ1 asks how aggregated and non-uniform hospital consumption records can be transformed into clinically coherent demand profiles for successive arboviral epidemics. RQ2 asks how these temporally explicit profiles affect the performance of an external pharmaceutical supply chain under a common network structure and a consistently applied stock-setting rule. RQ3 asks which inventory, monitoring, and post-epidemic management priorities emerge from the comparison of baseline, epidemic, and post-epidemic supply chain performance.

The study makes four contributions. First, it offers a transparent procedure for processing imperfect hospital pharmaceutical data without presenting them as diagnosis-specific prescriptions. Second, it links clinical classification to supply chain modelling, which prevents medicines with different indications and treatment phases from being aggregated indiscriminately. Third, it combines empirically calculated excess consumption with the temporal shape of official surveillance curves. Fourth, it defines an AnyLogistix experiment that compares baseline, Chikungunya, Zika, and post-epidemic conditions while maintaining a clear boundary between observed data and simulated logistics behaviour.

The remainder of the paper reviews the literature on pharmaceutical supply chain resilience and simulation, presents the French Guiana case, explains the empirical reconstruction and modelling protocol, reports the final AnyLogistix simulation results, and discusses their implications for resilience-oriented pharmaceutical planning.

4.2 Literature background

4.2.1 Pharmaceutical supply chain vulnerability and resilience

Pharmaceutical supply chains combine regulated production, quality assurance, specialised storage, transport, wholesale distribution, and care delivery. This structure creates interdependence across organisations and jurisdictions. Risks may originate from supplier concentration, production failure, transport disruption, regulatory constraints, demand uncertainty, or poor visibility across the network (Jaberidoost et al., 2013; Miller et al., 2021; Dolgui et al., 2020). The same event can also propagate through the chain. A local shortage may trigger substitution, accelerated ordering, or redistribution, creating secondary pressure on products that were not initially affected.

Resilience refers to the capacity to prepare for disruption, absorb its immediate effects, adapt operations, and restore acceptable performance. Quantitative studies represent these capacities through service, backlog, recovery time, inventory, network redundancy, and related measures

(Hosseini et al., 2019). The literature also distinguishes resilience from viability. Resilience concerns the response to disruption, whereas viability considers whether the supply chain can continue to serve its function under persistent or repeated changes in its environment (Ivanov, 2022, 2024). For healthcare, the distinction matters because a system may eventually fulfil orders yet still fail to deliver them within a clinically useful time.

Preparedness strategies include diversified sourcing, additional capacity, risk-based inventories, information sharing, and tested contingency plans (Belhadi et al., 2022; Bernus et al., 2020; Gebhardt et al., 2022; Shishodia et al., 2023). Their value depends on context. More inventory can protect service, but it also increases carrying cost, expiry exposure, and storage requirements. Redundancy can reduce dependence, yet it may be difficult for regulated products or small markets. A resilient policy must therefore connect the criticality and variability of a medicine to the lead time and recovery characteristics of its supply route.

4.2.2 Epidemic-driven demand and pharmaceutical distribution

Epidemics differ from many conventional supply disruptions because demand, supply, and operational capacity may change at the same time. Case incidence can rise within a short period, but pharmaceutical demand is filtered through symptoms, clinical protocols, access to care, and existing inventories. The resulting signal may be delayed, uneven across products, and difficult to distinguish from routine demand. Research conducted during COVID-19 showed that epidemic shocks can produce demand amplification, inventory depletion, delayed replenishment, and ripple effects even when a chain remains structurally intact (Chowdhury et al., 2021; Ivanov, 2020; Queiroz et al., 2020).

Consistent with Ivanov's ripple-effect perspective, disruption in a supply network should be analysed beyond the immediate event that triggers it. The issue is not only the magnitude of the initial shock, but also the way in which its consequences propagate through the network structure and remain embedded in operational states, including orders backlog, inventory depletion, and delayed replenishment. This perspective is particularly relevant for epidemic-driven pharmaceutical demand, where the end of the epidemiological peak does not necessarily coincide with the restoration of logistics equilibrium. It therefore justifies distinguishing independent scenario comparison from sequential recovery analysis (Ivanov & Dolgui, 2019; Dolgui et al., 2020).

Pharmaceutical retail and healthcare supply studies have mainly examined global pandemics, vaccines, or large national networks. Simulation studies show that sudden demand growth can reduce service and create backlog without a complete supply failure (Golan et al., 2021;

Schleifenheimer & Ivanov, 2024; Zaoui *et al.*, 2023). Arboviral epidemics have received much less attention from an operations perspective. They are often local or regional, production may continue elsewhere, and the principal pressure may occur at distribution and replenishment stages. These characteristics make them useful for isolating demand-side stress in geographically constrained supply chains.

Clinical differentiation is necessary in this setting. The recommended initial management of suspected Chikungunya and Zika is symptomatic, with paracetamol used for fever and pain. Aspirin and non-steroidal anti-inflammatory drugs should be avoided until dengue has been excluded because of bleeding risk (Pan American Health Organization, 2022). Chikungunya may later require stronger analgesics, anti-inflammatory treatment, or therapies used for neuropathic and persistent pain. Zika generally has a shorter symptomatic period and less persistent joint disease. A single generic category of "pain medicines" therefore cannot represent both epidemics adequately.

4.2.3 Simulation-based decision support and digital representations

Discrete-event simulation is suited to supply chains because orders, shipments, inventory updates, and replenishment decisions occur as events over time. It can test how a network behaves under alternative demand profiles without changing the real system. Simulation has been used to examine epidemic propagation through supply chains, inventory responses, and recovery strategies (Burgos & Ivanov, 2021; Ivanov, 2020; Schleifenheimer & Ivanov, 2024).

Digital twin terminology is sometimes applied broadly to simulation models. A strict digital twin normally requires repeated data exchange or synchronisation between the physical and digital systems. The model developed here does not meet that condition. It is therefore described as a simulation-based digital representation built from historical consumption records, epidemiological curves, and documented logistics parameters. This distinction avoids implying real-time integration while preserving the value of scenario-based decision support (Ivanov & Dolgui, 2019, 2021; Ivanov, 2023).

This distinction is also consistent with the digital supply chain twin (DSCT) literature, which treats a digital twin as more than an offline scenario model (Ivanov & Dolgui, 2021; Ivanov, 2023; Guo & Mantravadi, 2025). The present AnyLogistix model remains a conventional simulation-based representation because it is scenario-based, asynchronous, and disconnected from live operational data. A DSCT represents a technological break because it is dynamically fed by real-time field data from hospital information systems, IoT devices, and operational events, allowing closed feedback loops and continuous predictive analysis. In the present

article, this clarification prevents the model from being presented as a real-time twin while using the DSCT framework to interpret the limits of a static scenario-based simulation.

Digital decision support is especially useful when data are incomplete, provided that assumptions remain visible and expert knowledge does not become an unreported substitute for evidence (Furstenau et al., 2022; Traore et al., 2018). Explainability and human oversight are therefore part of model quality, not secondary features (Tchuente et al., 2024; Zaoui et al., 2026). In the present case, medical expertise determines which products are clinically plausible, while supply chain modelling examines the operational consequences of the reconstructed demand. Neither component can replace the other.

4.2.4 Research gap and analytical positioning

Three gaps emerge from the literature. First, most epidemic supply chain studies focus on COVID-19 and large-scale production or distribution interruptions. Less is known about successive regional epidemics that primarily affect downstream demand. Second, healthcare simulation studies often start from clean demand series, whereas real hospital records may be aggregated, non-uniform, and disconnected from diagnoses. Third, medical treatment structure is seldom incorporated into the preprocessing of supply chain demand.

This chapter responds by combining a clinically reviewed case analysis with a discrete-event simulation protocol. The unit of analysis is the external pharmaceutical supply chain serving the Andrée Rosemon Hospital Center. The empirical contribution lies in reconstructing demand from observed hospital issues. The modelling contribution lies in converting the reconstructed phase totals into monthly, scenario-specific profiles that can be tested under the same network structure.

4.3 Case context: French Guiana and successive arboviral epidemics

French Guiana is a French overseas territory on the north-eastern coast of South America. Its population is concentrated along the coast, while inland communities are dispersed across a large territory (de Thoisy et al., 2021; Fritzell et al., 2016). The health system must therefore combine central hospital capacity with remote and decentralised care. These spatial features also shape pharmaceutical logistics. Most medicines are supplied from outside the territory, and replenishment depends on air and maritime links before products enter wholesale and hospital distribution channels.

The Andrée Rosemon Hospital Center in Cayenne is the empirical focal point of the study. The dataset records quantities issued by the hospital pharmacy from 2013 to 2017. These records

reflect hospital pharmaceutical activity across all diagnoses. They do not identify the patient, indication, prescriber, care unit, or whether part of the treatment continued after discharge. The data remain useful because they provide a longitudinal record of hospital pharmacy issues across the study period, while the year-to-year extraction differences are addressed explicitly in the data-quality analysis.

The Chikungunya epidemic began in 2014 and continued into 2015. Official surveillance shows a gradual rise, sustained high activity, several peaks, and a prolonged decline rather than a single symmetric wave (Santé publique France, 2015; Staples et al., 2009). Approximately 16,000 clinically evocative cases were recorded over the full period (Santé publique France, 2015). The acute illness commonly produces fever and severe polyarthralgia, and a proportion of patients develop post-acute or chronic musculoskeletal symptoms (Bertolotti et al., 2020; McCarthy et al., 2022). This clinical course explains why analgesic demand can extend beyond the initial febrile episode.

The Zika epidemic followed in 2016. Surveillance identified approximately 9,700 clinically evocative cases, with the main activity concentrated between the beginning of the year and September (Santé publique France, 2016). Many infections are asymptomatic, and symptomatic cases are generally mild and short. Nevertheless, the epidemic created substantial public health concern because of neurological and congenital complications (Flamand et al., 2019). From a pharmaceutical perspective, the expected hospital demand is more concentrated in first-line analgesic and antipyretic treatment than in anti-inflammatory management.

The two epidemics therefore occurred in the same territory but created different therapeutic demand structures. Their succession also provides a post-epidemic observation year. The 2017 data can reveal whether some medicine classes remained above the 2013 reference, although the available records cannot identify whether that difference resulted from persistent Chikungunya symptoms, changes in prescribing, hospital activity, or unrelated clinical demand.

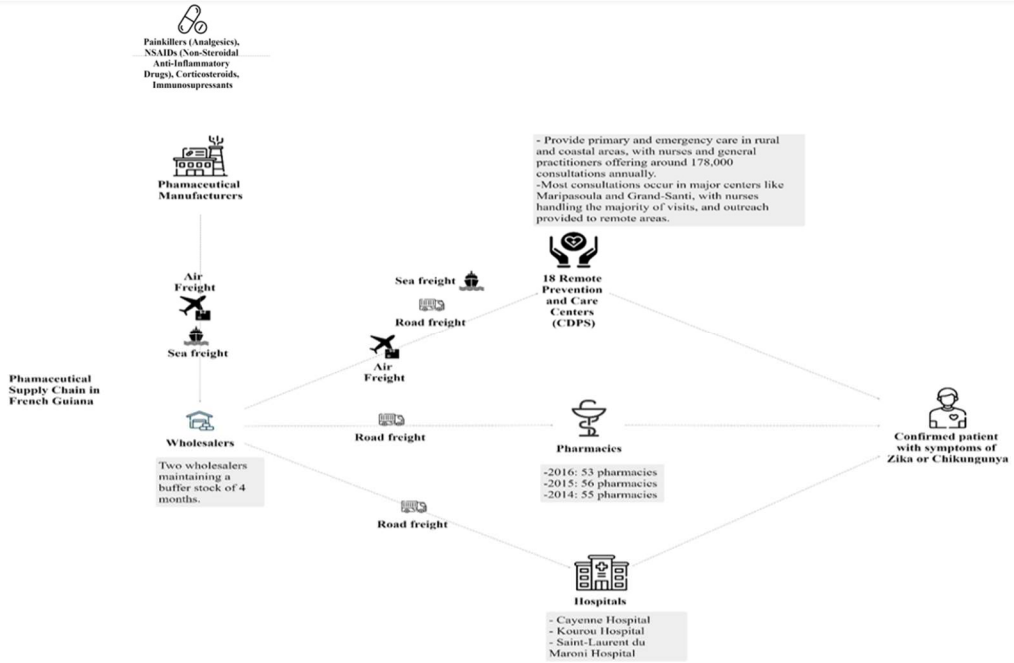


Figure 4.1: Simplified external pharmaceutical supply chain considered in the study.

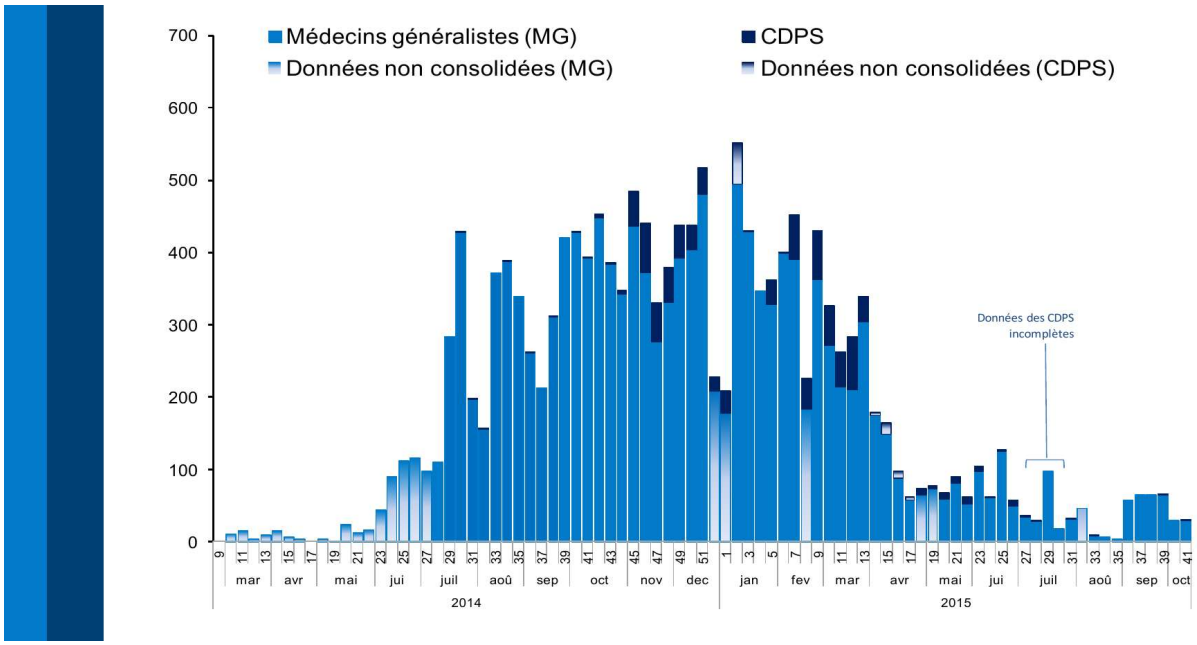


Figure 4.2: Weekly estimated Chikungunya syndromes in French Guiana, February 2014 to October 2015. (Santé publique France, 2015).

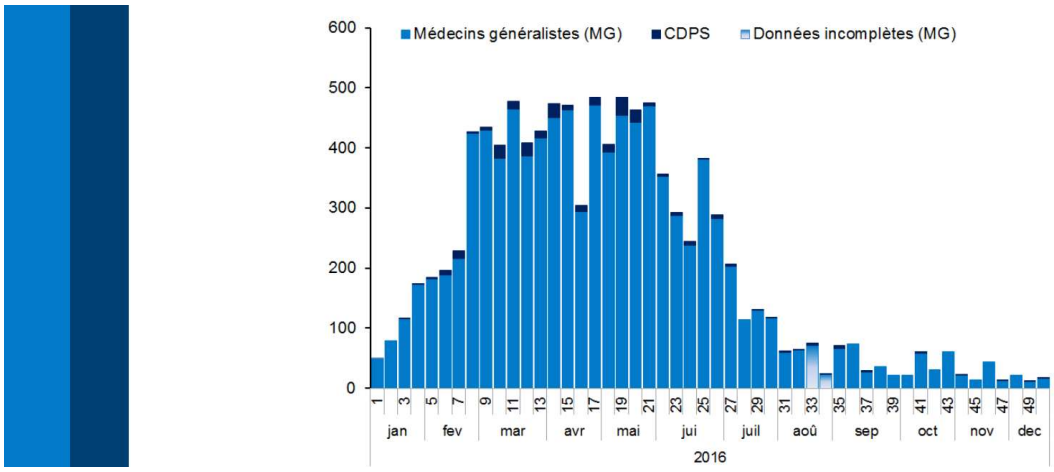


Figure 4.3: Weekly estimated Zika syndromes in French Guiana, 2016.

(Santé publique France, 2016).

4.4 Data and methodology

4.4.1 Research design and model boundary

The research follows a sequential case-study and simulation design. The first stage reconstructs disease-relevant demand from hospital consumption records. The second stage aligns the reconstructed quantities with the temporal development of each epidemic. The third stage introduces the resulting monthly demand into AnyLogistix and compares supply chain performance across four scenarios.

The empirical and simulated systems have different boundaries. Hospital issues are observed inside the healthcare system, but the simulation represents the external chain supplying the hospital. The model begins with upstream suppliers, passes through wholesalers or distributors, and ends at the hospital as the demand node. It does not represent prescriptions, patient trajectories, ward stockrooms, internal dispensing, outpatient pharmacies, or individual treatment adherence. This distinction prevents internal hospital practices from being inferred from external logistics outputs.

4.4.2 Data sources

Two data sources are combined. The first comprises annual hospital pharmacy issues from 2013 to 2017. Each record identifies a product and the annual quantity issued. Products include tablets, capsules, sachets, suppositories, and injectable forms. The generic term pharmaceutical unit is therefore used throughout the study. The second source comprises official weekly epidemiological bulletins for Chikungunya and Zika in French Guiana (Santé publique France, 2015, 2016).

The 2013 data are used as the pre-epidemic reference. The Chikungunya phase considers the 2014 and 2015 pharmacy records jointly because the epidemic crossed the calendar-year boundary and the source data are available as annual extractions rather than epidemic-window-specific series. The Zika comparison uses the available 2016 annual extraction, and 2017 represents the post-epidemic observation year. The temporal windows used in the simulation are specified separately in Sections 4.6 and 4.7.

4.4.3 Data quality, harmonisation, and interpretation

The hospital extractions were not uniform across years. Some products appear in one year and not another, and the number of references differs substantially. An absent product may represent zero use, a change in coding, or an omitted reference. For that reason, the analysis does not treat the full annual total as a directly comparable epidemiological measure.

The data are interpreted as aggregated hospital pharmacy activity. A positive difference during an epidemic phase is compatible with epidemic-associated excess use, but it cannot establish causality. A negative difference means that the observed quantity was below the 2013 reference. It does not mean that a patient consumed a negative quantity. The method therefore retains only positive differentials when constructing the epidemic-associated excess component. Negative values remain part of the descriptive audit but are set to zero in the excess-demand calculation.

This decision is analogous to an excess-event framework. The outcome of interest is whether the observed phase quantity exceeds the reference. The method does not claim that every excess unit was prescribed for Chikungunya or Zika. It identifies the positive volume that is both temporally associated with the epidemic phase and clinically compatible with the selected therapeutic class.

4.4.4 Clinical classification of medicines

The products were first separated into elementary therapeutic categories and then consolidated into model classes. Clinical review was performed before the logistics aggregation. This order is necessary because the same broad pharmacological family may have a different role in Zika, acute Chikungunya, and persistent Chikungunya pain.

Acetylsalicylic acid and antiplatelet products were introduced in the hospital extraction as a predefined false-control group. They are excluded from the demand scenarios. Their presence can reflect unrelated cardiovascular use and cannot be interpreted as recommended arboviral treatment. Corticosteroids are also excluded from the acute Chikungunya and Zika scenarios. They are retained only in the 2017 post-epidemic reconstruction, where persistent inflammatory

conditions may be more clinically plausible. Non-steroidal anti-inflammatory drugs are excluded from the Zika scenario and grouped with other anti-inflammatory treatments in the Chikungunya scenario. This choice follows the clinical caution required while dengue remains a possible diagnosis (Pan American Health Organization, 2022).

Scenario	Therapeutic classes retained	Main exclusions
2013 baseline	Step I analgesics; step II analgesics; grouped anti-inflammatory treatments; corticosteroids; neuropathic co-analgesics recorded as unavailable/zero in the 2013 extraction	Antiplatelet false-control group; narcotics and unrelated categories
CHIKV	Step I analgesics; step II analgesics including intermediate combinations; neuropathic co-analgesics; grouped anti-inflammatory treatments	Antiplatelets; corticosteroids; negative differentials
ZIKV	Step I analgesics; step II analgesics; neuropathic co-analgesics	Antiplatelets; corticosteroids; anti-inflammatory treatments; negative differentials
2017	Step I analgesics; step II analgesics; neuropathic co-analgesics; grouped anti-inflammatory treatments; corticosteroids	Antiplatelet false-control group; negative differentials

Table 4.1: Therapeutic grouping used in the analysis

For the scenario grouping, step II includes tramadol and intermediate paracetamol-tramadol combinations. Grouped anti-inflammatory treatments include non-steroidal anti-inflammatory drugs and the small positive differentials for colchicine and hydroxychloroquine in the Chikungunya phase.

4.4.5 Calculation of phase-level positive differentials

The empirical reconstruction did not generate theoretical prescriptions from epidemiological case counts. It used a direct comparison with the 2013 reference year. For each therapeutic class, the annual or phase-level quantity available for the scenario was compared with the 2013 reference quantity. A positive difference was retained only when the class was clinically relevant to the scenario. A negative difference remained part of the descriptive audit but was not introduced into AnyLogistix as negative demand. These differences are operational scenario inputs and are not time-normalised estimates of epidemic-attributable consumption.

For Chikungunya, the 2014 and 2015 pharmacy records were considered jointly because the epidemic crossed the calendar-year boundary and the available pharmacy data were annual rather than epidemic-window specific. For Zika, the available 2016 annual quantity was compared with the 2013 annual reference. For the post-epidemic scenario, the 2017 annual quantity was compared with 2013. The resulting positive differentials are used as scenario-construction values rather than causal estimates of disease-specific pharmaceutical use.

This rule preserves the arithmetic of the class-level comparisons while keeping the reconstruction readable. For example, in 2017, adult and adolescent step I analgesics increased from 651,190 units in 2013 to 759,619 units in 2017, yielding a retained differential of 108,429

units. By contrast, the paediatric step I subgroup decreased from 81,076 to 34,795 units. This negative difference was documented but not simulated as negative demand.

The Chikungunya differential is a phase-level operational differential rather than an annualised or time-normalised excess estimate. Combining the 2014 and 2015 records follows the epidemiological continuity of the epidemic across the calendar-year boundary and the annual granularity of the source data. The resulting differential is used only as a simulation input and should not be interpreted as a rate-adjusted estimate of epidemic-attributable consumption.

4.4.6 Epidemiological weighting and monthly demand construction

The hospital dataset determines the magnitude of the reconstructed demand component, but it does not provide monthly diagnosis-linked dispensing series. Official surveillance curves are therefore used only to place the retained positive differentials in time. The weekly bars from the epidemiological bulletins were digitised, aggregated by month, and normalised so that the monthly shares sum to 100% within each scenario. These monthly weights are not additional hospital observations and are not case-to-prescription conversion factors; they are temporal allocation factors.

Temporal allocation is required because AnyLogistix simulates orders and inventory positions over time. A uniform allocation would attenuate epidemic peaks, whereas assigning the entire excess to a single date would create an unrealistic one-off shock. The monthly weights therefore provide a controlled link between data sources: hospital pharmacy data define the magnitude of excess demand, while epidemiological surveillance defines its timing.

The principal Chikungunya profile covers July 2014 to July 2015, the period of strongest and sustained activity identified in the epidemiological curve. The Zika profile covers January to September 2016, corresponding to the main epidemic period and the official end of the epidemic in week 37.

For each month and each therapeutic class, the demand introduced into AnyLogistix was built by adding two components: the normal baseline demand estimated from 2013 and the share of retained positive differential assigned to that month. Because monthly baseline records were not available, the normal component was estimated by distributing the 2013 baseline evenly across months. This is an explicit modelling convention. Monthly allocations were implemented as integer quantities, with rounding adjusted so that class-level monthly sums matched the retained phase totals exactly.

The numbers of clinically evocative cases are used only as rough order-of-magnitude plausibility checks. Dividing the retained Chikungunya differential by approximately 16,000 reported cases gives 52.5 pharmaceutical units per reported case, while dividing the retained Zika differential by approximately 9,700 reported cases gives 14.07 units. These ratios are not patient-level treatment estimates because not all reported cases were hospitalised and hospital issues cover all indications. They are not used to calibrate the simulation and should be interpreted only as contextual plausibility checks.

4.4.7 AnyLogistix model and scenarios

AnyLogistix is used to implement a discrete-event representation of the external pharmaceutical supply chain. Discrete-event simulation is appropriate for this chapter because orders, shipments, deliveries, inventory depletion, and backlog are event-based processes that evolve over time. Comparable simulation studies have used this approach to examine epidemic disruptions, supply chain stress testing, and resilience responses in logistics and pharmaceutical settings (Ivanov, 2020; Burgos & Ivanov, 2021; Schleifenheimer & Ivanov, 2024). The comparative model links upstream suppliers, the SPG Pharmaceutical Wholesaler, and the Andrée Rosemon Hospital Center as the demand node. Internal prescriptions, ward stockrooms, outpatient pharmacies, and patient trajectories are not represented. This boundary is consistent with the available data, which record hospital pharmacy issues rather than individual treatments.

The platform was selected because it allows the same network structure to be tested under alternative demand profiles while tracking inventory position, backlog, expected lead-time service level, lead time, and distance travelled. Its use is consistent with prior work in which AnyLogistix supported baseline definition, disruption scenario design, KPI-based assessment, and comparative interpretation of supply chain response (Ivanov, 2020; Schleifenheimer & Ivanov, 2024). The primary comparative experiment contains four independent scenarios. The baseline scenario represents the 2013 pre-epidemic reference state. The Chikungunya scenario covers July 2014 to July 2015 and adds the weighted CHIKV positive differentials to the normal baseline demand over the same horizon. The Zika scenario covers January to September 2016 and uses the same construction with ZIKV-specific classes and weights. The 2017 scenario represents post-epidemic demand and includes corticosteroids and neuropathic co-analgesics. The scenarios are compared under the same distribution boundary so that performance differences can be interpreted as consequences of the reconstructed demand profiles.

The simulation uses aggregated therapeutic classes as products. This choice reduces unsupported product-level assumptions and matches the level at which the hospital data can be interpreted reliably. A later product-level disaggregation would be justified only if product-specific lead times, inventory policies, storage constraints, and demand series were documented.

For clarity, the four scenarios are hereafter denoted as S0 for the 2013 baseline scenario, S1 for the Chikungunya scenario, S2 for the Zika scenario, and S3 for the 2017 post-epidemic scenario.

Scenario	Simulation horizon	Demand structure	Purpose
Baseline (S0)	January-December 2013	2013 hospital baseline demand, entered as stable historical demand	Establish the pre-epidemic reference state and verify internal model consistency
CHIKV (S1)	July 2014-July 2015	13-month baseline demand plus weighted CHIKV positive differentials	Assess model response to a prolonged, multi-peak reconstructed demand profile
ZIKV (S2)	January-September 2016	9-month baseline demand plus weighted ZIKV positive differentials	Assess model response to a shorter, concentrated reconstructed demand profile
Post-epidemic (S3)	January-December 2017	Annual baseline demand plus positive 2017 differentials	Assess model response under an independent 2017 post-epidemic demand profile

Table 4.2: Simulation scenarios

4.4.8 Inventory setting and modelling buffer

The comparative simulations use a finite baseline stock configuration rather than a fully parameterised dynamic replenishment policy. The simulation uses the 2013 baseline as the reference stock configuration and examines the outputs generated when the reconstructed Chikungunya, Zika, and post-epidemic demand profiles are introduced under the same stock-setting rule.

In the simulation model, the Andrée Rosemon Hospital Center was represented as the demand point, while the reference stock was assigned to the external supply node represented by SPG Pharmaceutical Wholesaler. This stock was not treated as unlimited. For each therapeutic class, the reference quantity was constructed from the normal baseline demand corresponding to the simulated horizon and supplemented by a 30-day modelling buffer based on average 2013 demand. The 30-day value is a modelling convention applied consistently across the scenarios; it is not an empirically estimated safety-stock level and is not presented as an observed inventory policy of the hospital or the wholesaler.

No formal safety-stock calculation is used in the main experiment because the empirical dataset does not contain the daily demand variability, replenishment lead-time variability, storage constraints, expiry rules, or target service levels required for such an estimate. Dynamic replenishment and safety-stock optimisation are therefore outside the main experiment and are retained for future research. This separation keeps the demand-scenario comparison distinct from untested inventory-policy effects.

4.4.9 Performance indicators

The simulation results were evaluated using selected AnyLogistix performance indicators and compared with the 2013 baseline scenario. These indicators were chosen to assess both quantity-based pressure and time-based responsiveness within the simulated pharmaceutical supply chain. They include Demand (Products Backlog), Demand (Orders Backlog), Available Inventory Including Backlog, ELT Service Level by Products and Lead Time.

Demand (Products Backlog) measures the quantity of pharmaceutical units associated with orders that remain unfulfilled in the model. Demand (Orders Backlog) records the number of customer orders that remain open at the end of the simulation horizon. These two indicators are interpreted as logistics outputs. They do not represent untreated patients or clinical outcomes.

Available Inventory Including Backlog reflects the net inventory position after unmet demand has been considered. A positive value indicates that the simulated configuration still holds available stock at the system level. A negative value indicates that residual demand exceeds the available stock position. This indicator is therefore used to assess stock pressure in the simulated distribution layer; it is not interpreted as the physical inventory available on hospital wards.

ELT Service Level by Products measures the share of product demand delivered within the expected lead-time target. Lead Time records the delivery interval generated by the model within the represented distribution layer. The resilience assessment relies primarily on backlog, net inventory position, expected lead-time service level, and lead time.

The indicators are reported by scenario and, when relevant, by therapeutic class. A scenario is not considered resilient solely because part of the demand is eventually delivered. It is assessed according to whether backlog emerges, whether the net inventory position remains positive, and whether the expected lead-time service level remains close to the 2013 baseline.

Given the unequal duration of the simulated scenarios, cumulative products backlog may overstate or understate scenario severity when interpreted as an absolute volume. A time-normalised indicator, the Temporal Severity Ratio (RST), was therefore added to compare backlog pressure across scenarios on a common temporal basis. RST is calculated as monthly products-backlog velocity divided by average monthly demand, multiplied by 100. Monthly products-backlog velocity corresponds to Demand (Products Backlog) divided by the simulation horizon, while average monthly demand corresponds to total demand introduced into the model divided by the same horizon. This indicator complements the AnyLogistix outputs by accounting for the temporal scale bias between S1, S2, and S3.

4.4.10 Model consistency, plausibility checks, and simulation assumptions

Four checks support the internal consistency and plausibility of the experiment. First, arithmetic controls ensure that monthly allocations sum exactly to the retained phase totals. Second, clinical review verifies the inclusion and exclusion of therapeutic classes. Third, reconstructed quantities are compared with reported case counts only as an order-of-magnitude plausibility check. Fourth, the baseline scenario is required to produce a stable simulated reference before epidemic profiles are compared. These checks do not constitute external validation against historical logistics outcomes.

The model also involves simplifying assumptions. In particular, the CHIKV differential is constructed from combined annual 2014-2015 pharmacy records while the primary simulated CHIKV horizon covers July 2014 to July 2015. The Zika differential is calculated from the available 2016 annual extraction and then distributed over the January-September 2016 simulation horizon. These are explicit scenario-construction conventions rather than time-normalised estimates of epidemic-attributable consumption. The results should therefore be interpreted with regard to the selected epidemic windows, the temporal allocation procedure, the finite-stock configuration, and the other specified model settings. Alternative epidemic windows, replenishment policies, and a sequential Zika-to-2017 configuration are retained for future research.

4.4.11 Network memory and sequential simulation extension

The main experiment compares S0, S1, S2, and S3 as independent scenarios. This design preserves comparability across reconstructed demand states, but it does not capture the memory of the logistics network. Consistent with Ivanov's ripple-effect perspective, a disruption may propagate through the network structure and persist beyond the initial demand shock through

residual orders backlog, inventory depletion, and delayed replenishment (Ivanov & Dolgui, 2019; Dolgui et al., 2020). Following Magableh et al. (2024) the analysis of recovery trajectories and logistics-system nervousness requires attention to the persistence of previous disruptions. In the present setting, the statistical independence between S2 and S3 removes the topological memory of the network and prevents the direct measurement of residual ripple effects.

A sequential extension would therefore require transferring the final state of each scenario into the initial state of the following scenario. The minimum state variables to transfer are on-hand inventory by node, orders backlog, and pipeline inventory. This protocol would make it possible to model carry-over effects, disruption tails, time-to-recovery, and the recovery trajectory from the epidemic phase to the post-epidemic phase. It also clarifies why the current S3 scenario should be interpreted as an independent post-epidemic demand state rather than as a measured recovery path.

4.5 Empirical reconstruction of pharmaceutical demand

4.5.1 Baseline and positive phase differentials

Table 3 presents the harmonised inputs used to construct the four AnyLogistix scenarios. The 2013 column represents the normal annual quantities available from the hospital extraction after therapeutic grouping. The other columns report retained positive phase-level differentials after clinical filtering. These differentials are not raw annual totals. They are the additional quantities added to the corresponding baseline demand before simulation.

Therapeutic class	2013 baseline	CHIKV positive differential	ZIKV positive differential	2017 positive differential
Analgesics, step I	732,266	661,394	119,265	108,429
Analgesics, step II (intermediate combinations included)	119,065	110,091	13,903	12,032
Neuropathic co-analgesics	0	36,490	3,325	34,860
Grouped anti-inflammatory treatments	45,081	32,018	0	3,392
Corticosteroids	29,773	0	0	7,663
TOTAL	**926,185**	**839,993**	**136,493**	**166,376**

Table 4.3: Harmonised pharmaceutical quantities used in the simulation scenarios

The zero value for neuropathic co-analgesics in 2013 reflects absence from the available extraction and is treated as a data limitation, not proof of zero clinical use. Corticosteroids are not included in the acute epidemic scenarios. For 2017, grouped anti-inflammatory treatments include the retained positive differentials for NSAIDs and hydroxychloroquine/Plaquenil; Colchicine/Colchimax are not retained in the 2017 reconstruction.

The Chikungunya excess total of 839,993 units is dominated by step I analgesics, followed by step II analgesics, neuropathic co-analgesics, and grouped anti-inflammatory treatment. This distribution is consistent with a condition characterised by severe pain and possible persistent musculoskeletal symptoms. It does not imply that each affected person received all four classes.

The Zika excess total of 136,493 units is concentrated in step I analgesics. Step II analgesics and neuropathic co-analgesics account for smaller positive differentials. Anti-inflammatory treatment is not introduced into the Zika demand scenario. The post-epidemic excess total is 166,376 units. The neuropathic co-analgesic value of 34,860 units reconciles the 2017 class sum with the retained total.

4.5.1.1 Detailed Chikungunya reconstruction

The Chikungunya scenario was reconstructed by considering the 2014 and 2015 pharmacy records jointly because the epidemic crossed the calendar-year boundary and the available pharmacy data were annual rather than epidemic-window specific. The retained CHIKV differential therefore corresponds to the positive arithmetic difference between the combined 2014-2015 phase quantity and the 2013 reference after exclusion of false controls, narcotics, corticosteroids, and negative differentials. This phase-level value is an operational scenario input and is not a time-normalised estimate of epidemic-attributable consumption.

Therapeutic class retained in CHIKV	Combined 2014-2015 quantity used for the bridge	2013 reference	Arithmetic difference	Modelling decision and retained value
Step I analgesics	1,393,660	732,266	+661,394	Retained as first-line symptomatic treatment. Retained = 661,394.
Step II analgesics, including intermediate combinations	229,156	119,065	+110,091	Retained for stronger pain management. Retained = 110,091.
Neuropathic co-analgesics	36,490	Not identifiable in 2013 extraction	+36,490	Retained with explicit data limitation. Retained = 36,490.
Grouped anti-inflammatory treatments	77,099	45,081	+32,018	Retained for CHIKV. Components: NSAIDs, Colchicine/Colchimax, Plaquenil. Retained = 32,018.
Retained CHIKV positive differential				661,394 + 110,091 + 36,490 + 32,018 = 839,993 pharmaceutical units.

Table 4.4: Detailed reconstruction of the CHIKV positive differential

This reconstruction explains why the simulated CHIKV demand is larger than the excess value alone. The AnyLogistix input combines the retained 839,993-unit CHIKV excess with the normal 2013 baseline demand prorated over the 13-month epidemic horizon. The resulting scenario demand is 1,811,106 pharmaceutical units.

4.5.1.2 Detailed Zika reconstruction

The Zika scenario was reconstructed separately because its clinical profile and therapeutic composition differ from Chikungunya. The simulation horizon covers January to September 2016, while the retained positive differential is calculated from the available 2016 annual pharmacy extraction relative to the 2013 annual reference and then distributed across the simulation horizon using the epidemiological weights. The active classes are step I analgesics, step II analgesics, and neuropathic co-analgesics. Anti-inflammatory treatments and corticosteroids are not introduced into the Zika demand scenario, consistent with the clinical caution required while dengue remains a differential diagnosis and with the shorter symptomatic profile of Zika.

Therapeutic class retained in ZIKV	2016 quantity used for the bridge	2013 reference	Arithmetic difference	Modelling decision and retained value
Step I analgesics	851,531	732,266	+119,265	Retained as main symptomatic treatment. Retained = 119,265.
Step II analgesics	132,968	119,065	+13,903	Retained as smaller pain-management component. Retained = 13,903.
Neuropathic co-analgesics	3,325	Not identifiable in 2013 extraction	+3,325	Retained with explicit data limitation. Retained = 3,325.
Grouped anti-inflammatory treatments	Not retained	45,081	0	Excluded from ZIKV active demand. Retained = 0.
Corticosteroids	Not retained	29,773	0	Excluded from acute ZIKV demand. Retained = 0.
Retained ZIKV positive differential				119,265 + 13,903 + 3,325 = 136,493 pharmaceutical units.

Table 4.5: Detailed reconstruction of the ZIKV positive differential

The Zika excess is therefore smaller than the CHIKV excess and affects fewer classes. The simulated Zika demand combines this retained 136,493-unit excess with the nine-month share of the normal 2013 baseline demand, giving an AnyLogistix input of 774,992 pharmaceutical units.

4.5.1.3 Detailed 2017 post-epidemic reconstruction

The 2017 scenario required an explicit post-epidemic reconstruction because several groups had to be separated before simulation: retained therapeutic groups, false controls, negative differentials, and products not retained for this phase. Table 6 reports the arithmetic bridge between the 2017 hospital quantities, the 2013 reference quantities, the raw differences, and the retained differentials used for the post-epidemic scenario.

Group or subgroup in the empirical reconstruction	2017 quantity	2013 reference	Arithmetic difference	Modelling decision and retained value
Antiplatelet agents (Aspegic/Kardegic)	28,448	2,688	+25,760	False control; excluded. Retained = 0.
Corticosteroids	37,436	29,773	+7,663	Retained for post-epidemic reconstruction. Retained = 7,663.
Amino-4-quinolines / hydroxychloroquine (Plaquenil)	2,442	560	+1,882	Retained within grouped anti-inflammatory treatments. Retained = 1,882.
NSAIDs	46,031	44,521	+1,510	Retained within grouped anti-inflammatory treatments. Retained = 1,510.
Colchicine / Colchimax	Not retained	Not retained	0	Not retained in 2017 reconstruction. Retained = 0.
Neuropathic co-analgesics	34,860	Not identifiable in 2013 extraction	+34,860	Retained with explicit data limitation. Retained = 34,860.
Step I analgesics, paediatric subgroup	34,795	81,076	-46,281	Negative difference; excluded. Retained = 0.
Step I analgesics, adults/adolescents	759,619	651,190	+108,429	Clinically retained. Retained = 108,429.
Intermediate step I-II analgesics	48,320	55,114	-6,794	Negative difference; excluded. Retained = 0.
Step II analgesics	75,983	63,951	+12,032	Clinically retained. Retained = 12,032.
Retained post-epidemic differential				108,429 + 12,032 + 34,860 + 7,663 + 1,882 + 1,510 = 166,376 pharmaceutical units.

Table 4.6: Detailed reconstruction of the 2017 post-epidemic differential

The arithmetic reconciliation is therefore explicit. The positive increase before excluding the false-control group is 192,136 units. Subtracting the antiplatelet false-control increase of 25,760 units gives the retained post-epidemic differential of 166,376 units. This value is the post-

epidemic excess input. It is added to the 2013 baseline to build the S3 operational demand of 1,092,561 pharmaceutical units in AnyLogistix.

Consequently, S3 should not be read as a raw 2017 annual total. It represents the clinically filtered post-epidemic pressure relative to 2013. The simulated backlog and inventory position then measure how the baseline stock configuration responds to this retained pressure.

4.5.2 Temporal demand profiles

Tables 7 and 8 present the normalised monthly allocation coefficients derived from the official epidemiological surveillance curves. These coefficients do not represent monthly hospital consumption or case counts. Their role is to distribute the retained class-specific excess demand over the relevant epidemic horizon. In this procedure, the hospital pharmacy data determine the magnitude of the reconstructed excess demand, while the epidemiological curves determine its temporal distribution. This preserves the exact phase-level totals used in the simulation and introduces the timing of each epidemic without treating surveillance data as prescription data.

Month	CHIKV monthly allocation coefficients
Jul 2014	6.77%
Aug 2014	7.68%
Sep 2014	7.37%
Oct 2014	12.25%
Nov 2014	8.99%
Dec 2014	9.33%
Jan 2015	11.24%
Feb 2015	8.45%
Mar 2015	6.89%
Apr 2015	3.39%
May 2015	1.70%
Jun 2015	6.33%
Jul 2015	9.62%
TOTAL	**100.00%**

Table 4.7: Monthly allocation coefficients for the principal Chikungunya scenario

The principal Chikungunya scenario covers July 2014 to July 2015, corresponding to the selected period of strongest and sustained epidemic activity used for the main simulation experiment.

Month	ZIKV monthly allocation coefficients
Jan 2016	4.36%
Feb 2016	10.74%
Mar 2016	22.29%
Apr 2016	17.81%
May 2016	18.71%
Jun 2016	16.19%

Month	ZIKV monthly allocation coefficients
Jul 2016	5.86%
Aug 2016	2.24%
Sep 2016	1.79%
TOTAL	**100.00%**

Table 4.8: Monthly allocation coefficients for the Zika scenario

The Zika scenario covers January to September 2016, consistent with the principal epidemic period.

4.5.3 Interpretation of the reconstructed demand

Because the Chikungunya epidemic crossed the calendar-year boundary, the 2014 and 2015 pharmacy records were treated as a single empirical phase before the scenario differential was constructed. This phase-level treatment aligns the annual source records with the epidemiological episode rather than treating the two calendar years as independent events. The resulting differential is used as an operational simulation input and is not interpreted as a time-normalised causal excess.

The Zika differential is smaller than the Chikungunya differential and is concentrated in fewer retained classes. This pattern is clinically compatible with the shorter symptomatic profile of Zika, but the reconstructed quantities remain scenario inputs rather than disease-attributable prescriptions. The post-epidemic pattern, particularly the positive differentials for neuropathic co-analgesics and corticosteroids, is compatible with continued or changing pain management but cannot be attributed uniquely to Chikungunya. It is therefore modelled as an independent post-epidemic demand condition rather than as confirmed chronic Chikungunya treatment.

These findings answer RQ1 at the data-construction level. Aggregated hospital records can be transformed into usable supply chain scenario inputs when clinical filtering, temporal alignment, and explicit treatment of negative differences are applied. The procedure preserves the distinction between the empirical records, the reconstructed demand component, and the quantities introduced into the simulation.

4.6 Simulation results

The four scenarios were compared by distinguishing between demand-construction values and simulation outputs. The simulation horizon, the total demand introduced into the model, and the retained positive differential embedded in each scenario describe how the demand scenarios were constructed. These values were derived from the reconstructed hospital pharmacy consumption data and introduced into AnyLogistix as input-control values. In contrast, Demand

(Products Backlog), Demand (Orders Backlog), Available Inventory Including Backlog, Lead Time, and ELT Service Level by Products are simulation outputs generated by the model.

KPI	S0 baseline 2013	S1 CHIKV 2014–2015	S2 ZIKV 2016	S3 post-epidemic 2017
Simulation horizon	Jan–Dec 2013	Jul 2014–Jul 2015	Jan–Sep 2016	Jan–Dec 2017
Demand introduced (input-control value)	926,185 pharmaceutical units	1,811,106 pharmaceutical units	774,992 pharmaceutical units	1,092,561 pharmaceutical units
Retained positive differential embedded in the scenario	0 pharmaceutical units	839,993 pharmaceutical units	136,493 pharmaceutical units	166,376 pharmaceutical units
Demand (Products Backlog)	0 pharmaceutical units	38,226 pharmaceutical units	76,659 pharmaceutical units	122,079 pharmaceutical units
Demand (Orders Backlog)	Not reported; no product backlog observed	6 orders	11 orders	16 orders
Available Inventory Including Backlog	152,248 pharmaceutical units	313,208 pharmaceutical units	-66,521 pharmaceutical units	-90,252 pharmaceutical units
Lead Time	2 days	1.5 days	1 day	2 days
ELT Service Level by Products	1.000	0.978	0.901	0.965

Table 4.9: Comparative summary of input-control values and AnyLogistix simulation outputs across the four scenarios.

The demand totals and retained positive differentials are input-control values derived from the reconstructed hospital pharmacy data. The remaining indicators are AnyLogistix simulation outputs. Backlog indicators are interpreted as logistics outputs and do not represent untreated patients. Available Inventory Including Backlog reflects a system-level net inventory position after unmet demand has been considered; it should not be interpreted as physical stock available on hospital wards.

To account for temporal-scale bias, Demand (Products Backlog) was normalised by simulation horizon. The calculation shows that S3 is the most critical scenario after temporal normalisation. Its monthly products-backlog velocity equals 10,173.25 pharmaceutical units per month and its RST equals 11.17%, compared with 8,517.67 units per month and 9.89% for S2, and 2,940.46 units per month and 2.11% for S1.

Scenario	Horizon	Demand	Products backlog	Backlog velocity / month	Average monthly demand	RST
S1 CHIKV	**13 months**	**1,811,106**	**38,226**	**2,940.46**	**139,315.85**	**2.11%**
S2 ZIKV	**9 months**	**774,992**	**76,659**	**8,517.67**	**86,110.22**	**9.89%**
S3 Post-epidemic	**12 months**	**1,092,561**	**122,079**	**10,173.25**	**91,046.75**	**11.17%**

Table 4.10: Temporal normalisation of products backlog across asymmetric simulation horizons.

Table 9 provides the cross-scenario overview. Sections 6.1-6.4 report the scenario-specific outputs, while Section 6.5 examines the correspondence between the reconstructed empirical demand and the simulated response.

4.6.1 Baseline reference scenario

The baseline scenario provides the pre-epidemic reference state for the comparative experiment. The model introduced 926,185 pharmaceutical units, corresponding to the 2013 hospital baseline after clinical grouping. No product backlog was observed, the ELT service level by products was 1.000, and Available Inventory Including Backlog remained positive at 152,248 pharmaceutical units. The local lead time was 2 days. These outputs establish a stable simulated reference under the specified baseline assumptions.

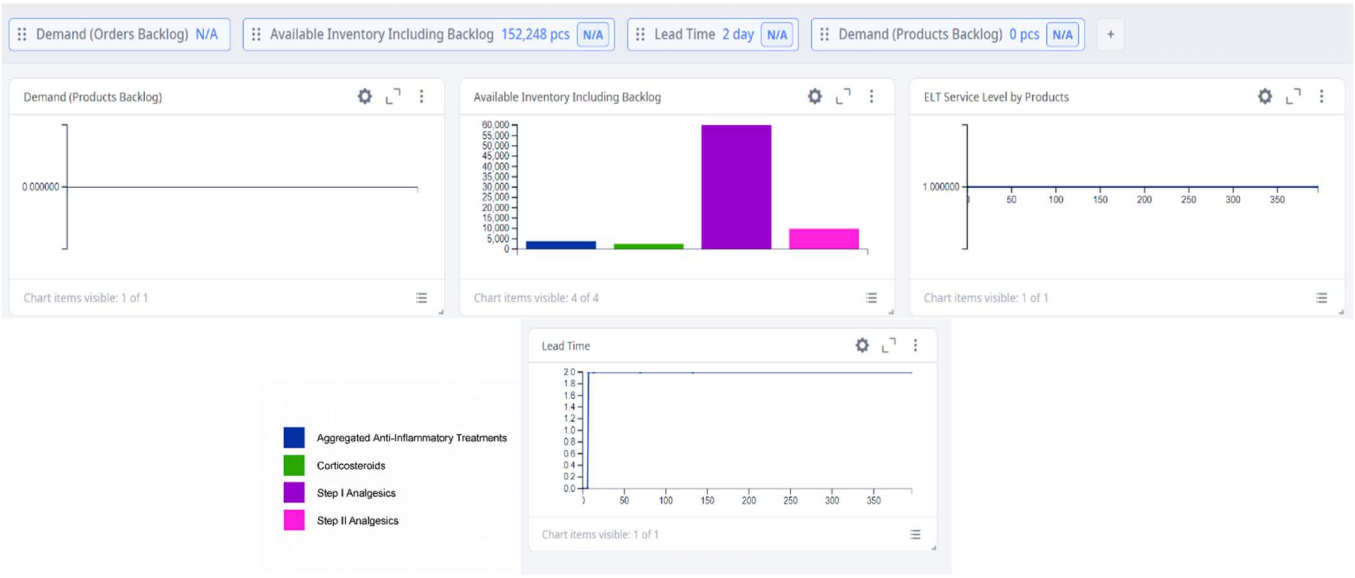


Figure 4.4: AnyLogistix dashboard for the 2013 baseline scenario.

The baseline anchors the comparative design. The absence of product backlog and the positive net inventory position in S0 provide the reference against which CHIKV, ZIKV, and the independent 2017 post-epidemic scenario are compared. This serves as an internal consistency check and should not be interpreted as external validation of historical logistics performance.

4.6.2 Chikungunya scenario

The CHIKV scenario introduced 1,811,106 pharmaceutical units over the 13-month period from July 2014 to July 2015. This total combines the prorated normal baseline demand with the retained CHIKV positive differential of 839,993 units. The simulation produced a product backlog of 38,226 units and 6 backlogged orders. The ELT service level remained high at 0.978, and the local lead time was 1.5 days.

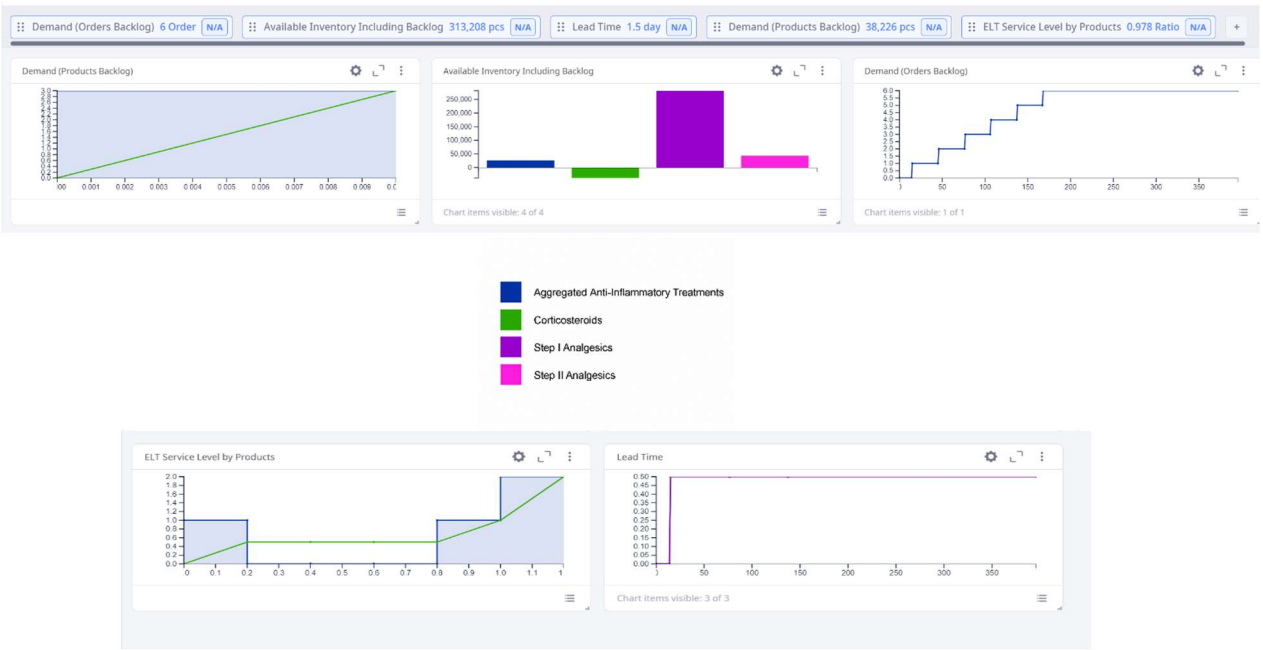


Figure 4.5: AnyLogistix dashboard for the Chikungunya scenario.

Under S1, the largest reconstructed demand input produced 38,226 pharmaceutical units of product backlog and six backlogged orders, while the net inventory position remained positive and the ELT service level was 0.978. The scenario includes step I analgesics, step II analgesics, neuropathic co-analgesics, and grouped anti-inflammatory treatments. The relationship between aggregate input volume and backlog is not proportional across the four scenarios. Scenario timing, therapeutic composition, and the specified stock configuration vary jointly, and the present design does not estimate the independent contribution of each factor.

4.6.3 Zika scenario

The ZIKV scenario introduced 774,992 pharmaceutical units from January to September 2016. This total combines the 9-month baseline demand with the retained ZIKV positive differential of 136,493 units. The active classes were step I analgesics, step II analgesics, and neuropathic co-analgesics. Anti-inflammatory treatments and corticosteroids were excluded from the active ZIKV demand scenario.

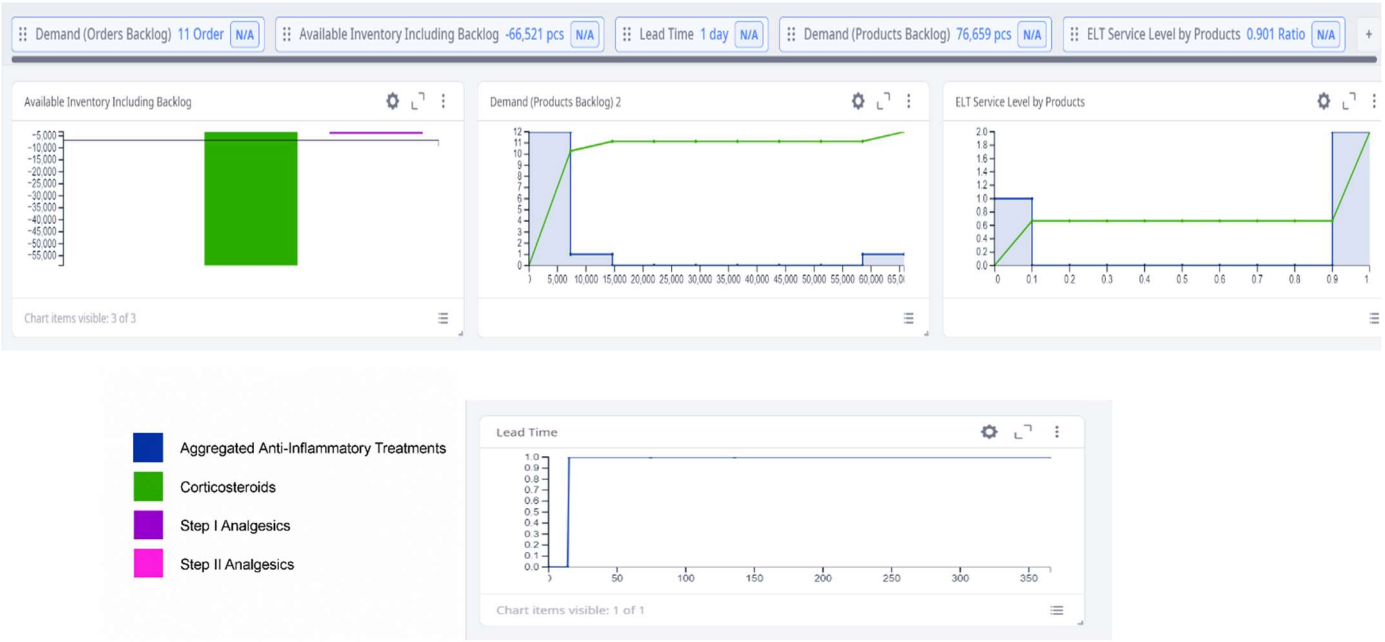


Figure 4.6: AnyLogistix dashboard for the ZIKV scenario.

The simulation generated a product backlog of 76,659 pharmaceutical units and 11 backlogged orders. Available Inventory Including Backlog was -66,521 units, the ELT service level was 0.901, and the local lead time was 1 day. The 2013 reference quantity for neuropathic co-analgesics was not identifiable in the available extraction. This is treated as a data limitation and not as evidence of zero historical stock or zero clinical use.

Compared with S1, S2 combines lower aggregate demand with a higher product backlog, a negative net inventory position, and a lower ELT service level. Because therapeutic composition, temporal allocation, and stock exposure differ jointly across the scenarios, these outputs are interpreted as scenario-level differences rather than evidence of a single causal mechanism. The comparison supports examining therapeutic-class structure in addition to aggregate demand.

From a DSCT perspective, this behaviour reflects a structural-complexity paradox. Although S2 introduces a lower aggregate demand than S1, it changes the therapeutic composition of demand and concentrates pressure on a narrower product mix. The decline of the ELT service level to 0.901 should therefore not be interpreted as a simple volume effect. It is better understood as a structural effect, in which fine-grained changes in therapeutic clusters expose specific stock and replenishment constraints that remain hidden in macro-level demand totals.

4.6.4 Post-epidemic 2017 scenario

The independent 2017 scenario introduced 1,092,561 pharmaceutical units. This total combines the annual 2013 baseline demand with the retained positive post-epidemic differential of 166,376 units reconstructed in Table 6. The retained 2017 differential includes adult/adolescent step I analgesics, step II analgesics, neuropathic co-analgesics, NSAIDs and hydroxychloroquine/Plaquenil within grouped anti-inflammatory treatments, and corticosteroids. The antiplatelet false-control group, Colchicine/Colchimax, and negative differentials were excluded.

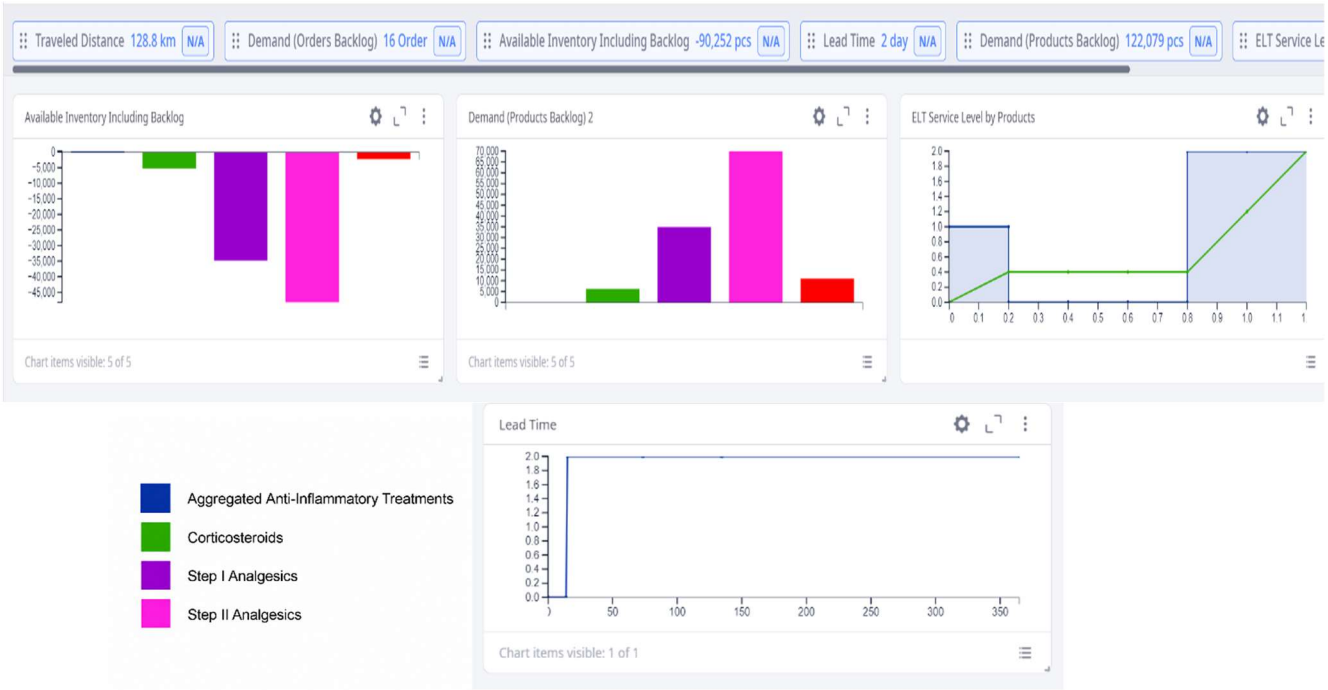


Figure 4.7: AnyLogistix dashboard for the 2017 post-epidemic scenario.

The simulation produced 122,079 pharmaceutical units of product backlog and 16 backlogged orders. Available Inventory Including Backlog was -90,252 units, the local lead time was 2 days, and the ELT service level by products was 0.965. These outputs differ from the S0 reference configuration: backlog is present and the net inventory position is negative, while the ELT service level is higher than in S2. Corticosteroids and neuropathic co-analgesics are included in the reconstructed 2017 demand profile, but the available data do not allow their positive differentials to be attributed uniquely to Chikungunya or Zika.

S3 is therefore interpreted as an independent post-epidemic demand state rather than as a measured recovery trajectory. It does not inherit backlog or inventory from S2. A sequential ZIKV-to-2017 experiment would constitute a separate extension capable of examining carry-over and recovery dynamics directly.

Temporal normalisation confirms the critical behaviour of S3. When Demand (Products Backlog) is normalised by scenario duration, S3 presents the highest monthly products-backlog velocity and the highest Temporal Severity Ratio (RST). This result supports the interpretation of the post-epidemic scenario as a second-cycle disruption. Consistent with Ivanov's ripple-effect perspective, this behaviour can be discussed as the possible propagation and persistence of an earlier disruption through the logistics network, expressed through residual backlog, depleted stock positions, and delayed replenishment. Supply-chain recovery and nervousness research supports the need to account for recovery strategies and system disturbance after a disruption (Magableh & Mistarihi, 2024; Magableh et al., 2024), while Ivanov's ripple-effect framework explains why this depletion should be interpreted dynamically as a propagated disruption rather than as an isolated 2017 demand state. Because S3 remains independent in the present model, this interpretation is consistent with residual ripple-effect logic but does not constitute a direct measurement of the ripple effect.

4.6.5 Empirical-to-simulation consistency

The consistency between the reconstructed empirical demand patterns and the simulation results was examined across the four scenarios. The objective was not to reproduce historical logistics outcomes exactly, since detailed historical observations of inventory shortages, order backlogs, and delivery performance were unavailable. Instead, the analysis examined whether the simulated responses were directionally consistent with the reconstructed differences in the demand inputs.

The baseline scenario represents the reference state. With no retained epidemic-related positive differential, S0 generated no product backlog, maintained a positive net inventory position, and achieved an ELT service level of 1.000. S1 generated product and order backlogs while maintaining a positive net inventory position and an ELT service level of 0.978. S2 generated a larger backlog, a negative net inventory position, and the lowest ELT service level among the four scenarios, at 0.901. In S3, backlog increased further and the net inventory position was -90,252 pharmaceutical units, while the ELT service level was 0.965, higher than in S2.

The simulated responses are directionally consistent with the heterogeneous demand patterns used to construct the scenarios. Similar or lower aggregate demand volumes are associated with different combinations of backlog, net inventory position, and ELT service level. Because therapeutic composition, temporal allocation, and stock exposure vary jointly across the scenarios, the comparison supports scenario-level empirical consistency rather than attribution of the outputs to a single mechanism. The simulation therefore provides a system-level representation of the reconstructed demand conditions rather than a direct reconstruction of historical logistics outcomes.

Scenario	Empirical signal retained	Simulation demand	Main simulated response	Interpretation
S0 baseline	2013 pre-epidemic demand	926,185 Pharmaceutical units	No product backlog; ELT = 1.000	Stable reference state
S1 CHIKV	Largest positive differential, 839,993 Pharmaceutical units	1,811,106 Pharmaceutical units	38,226 Pharmaceutical units backlog; 6 backlogged orders; ELT = 0.978	Backlog present; net inventory remained positive; ELT = 0.978
S2 ZIKV	Positive differential, 136,493 pharmaceutical units	774,992 Pharmaceutical units	76,659 Pharmaceutical units backlog; 11 backlogged orders; ELT = 0.901	Higher backlog and negative net inventory position; lowest ELT among the four scenarios
S3 2017	Post-epidemic positive differential, 166,376 Pharmaceutical units	1,092,561 Pharmaceutical units	122,079 Pharmaceutical units backlog; 16 backlogged orders; inventory position = -90,252 Pharmaceutical units; ELT = 0.965	Highest backlog and negative net inventory position; ELT higher than in S2

Table 4.11: Empirical-to-simulation correspondence between reconstructed pharmaceutical demand and simulated supply chain response

The empirical-to-simulation correspondence can be traced through three elements. First, the demand introduced into each AnyLogistix scenario corresponds directly to the reconstructed hospital-based demand input: 926,185 pharmaceutical units in S0, 1,811,106 in S1, 774,992 in S2, and 1,092,561 in S3. Second, backlog is absent in S0 and present in S1-S3, while the net inventory position is negative

in S2 and S3. Third, the pharmaceutical composition of each scenario follows the therapeutic-class filtering defined during the empirical reconstruction.

This correspondence provides traceability between the empirical data and the simulation experiments. It should not, however, be interpreted as statistical validation of the model or as evidence of patient-level causality. With four scenario observations and no historical logistics series for backlog, negative net inventory position, or ELT performance, the comparison supports directional empirical consistency rather than formal statistical correlation.

4.7 Discussion

4.7.1 From hospital consumption records to simulated demand

The first research issue concerns the transformation of aggregated hospital pharmacy records into demand scenarios that remain clinically plausible and operationally interpretable. The results show that this transformation requires a clear separation between observed consumption, reconstructed epidemic-associated excess, and simulated logistics behaviour.

The empirical reconstruction first identifies pharmaceutical consumption that is clinically compatible with the therapeutic profiles retained for chikungunya and Zika. Positive phase-level differentials relative to the 2013 reference are then used to represent additional demand pressure. These quantities are scenario inputs rather than estimates of disease-attributable consumption. This distinction is particularly important because the original pharmacy records are not linked to diagnoses, patients, wards, or individual prescriptions.

The baseline scenario provides an internal consistency check for this procedure. Under the 2013 demand profile, the model generated no product backlog, maintained a positive net inventory position, and achieved an ELT service level of 1.000. The simulation therefore did not generate artificial logistics stress under the reference demand configuration. This result does not constitute external validation of the model. It establishes that the common network and baseline demand configuration produce a stable reference against which the epidemic and post-epidemic scenarios can be compared.The decision to retain positive differentials serves a different methodological purpose. It isolates additional pharmaceutical demand relative to the pre-epidemic reference while preventing decreases in unrelated or incompletely extracted product categories from offsetting increases in clinically relevant medicines. Negative differentials remain informative in the descriptive analysis, but they are not interpreted as negative epidemic

demand. This procedure preserves the distinction between data reconstruction and simulation response.

Temporal allocation adds a second dimension to the reconstruction. Demand quantities distributed differently over time can expose the simulated supply chain to different operating conditions. Weighting the reconstructed positive differentials according to epidemic timing therefore represents both the amount of additional demand introduced into the scenario and its concentration over the selected horizon. This approach is consistent with simulation-based resilience research, in which disruption magnitude and temporal exposure are examined jointly (Ivanov, 2020; Hosseini et al., 2019).

4.7.2 Scenario-dependent pharmaceutical supply chain resilience

The comparison of the four scenarios shows that aggregate pharmaceutical demand alone does not explain supply chain performance. The chikungunya scenario contains the largest reconstructed positive differential, at 839,993 pharmaceutical units, and the largest total demand introduced into the model, at 1,811,106 units. Nevertheless, its product backlog of 38,226 units remains below the backlog generated by both the Zika and 2017 scenarios. Its ELT service level also remains high at 0.978.

The Zika scenario presents a different performance pattern. Total simulated demand is lower, at 774,992 pharmaceutical units, and the reconstructed positive differential is substantially smaller, at 136,493 units. Despite this lower aggregate volume, the scenario generates 76,659 units of product backlog, 11 backlogged orders, a negative net inventory position, and the lowest ELT service level among the four scenarios, at 0.901.

These results show that excess volume alone does not summarise scenario performance. Temporal allocation, therapeutic composition, and stock exposure differ simultaneously across the scenarios, and the current design does not isolate their independent effects. The comparison therefore supports a demand-structure interpretation of pharmaceutical supply chain resilience while remaining at the scenario level.

The 2017 scenario further illustrates this point. It contains a retained positive differential of 166,376 pharmaceutical units and generates the highest product backlog, at 122,079 units, together with 16 backlogged orders and a net inventory position of -90,252 units. At the same time, the ELT service level reaches 0.965, which is higher than under the Zika scenario.

The RST calculation reinforces this interpretation. S3 reaches 11.17%, compared with 9.89% for S2 and 2.11% for S1. When Demand (Products Backlog) is normalised by scenario duration, the post-epidemic scenario is not only the scenario with the largest cumulative products backlog; it is also the scenario with the strongest backlog pressure relative to its monthly demand base.

This result is consistent with a second-cycle disruption logic and can be interpreted in light of Ivanov's ripple-effect perspective. Although the acute epidemic signal has ended, the system may remain exposed to propagated disruption effects, including stock-rebuilding requirements, backlog absorption, pipeline imbalance, and rigid procurement conditions. The current experiment cannot measure this mechanism as a sequential recovery trajectory because S3 does not inherit the final state of S2. It shows only that the independently reconstructed post-epidemic demand state remains highly disruptive after temporal normalisation and is compatible with a residual ripple-effect mechanism.

An ELT service level that remains comparatively high can coexist with accumulated backlog and a negative net inventory position. ELT service level captures one dimension of fulfilment performance, while backlog and net inventory position describe different quantity-based outcomes. The indicators are therefore interpreted jointly when examining simulated disruption response, consistent with quantitative resilience research (Hosseini et al., 2019; Ivanov, 2022).

The 2017 experiment must nevertheless be interpreted carefully. It is an independent post-epidemic state scenario rather than a sequential continuation of the Zika simulation. It therefore does not reproduce the physical carry-over of Zika backlog or inventory from 2016 into 2017. What it shows is that the reconstructed 2017 demand profile, when applied to the common network configuration, does not reproduce the stable performance observed under the 2013 baseline. The result supports a post-epidemic perspective, but it should not be interpreted as a measured recovery trajectory.

4.7.3 Positioning the findings within supply chain resilience research

The findings complement previous epidemic supply chain studies in several ways. Simulation studies conducted in the COVID-19 context have shown that simultaneous demand, supply, capacity, and transportation disruptions can propagate through supply networks and delay

recovery (Ivanov, 2020; Burgos & Ivanov, 2021; Schleifenheimer & Ivanov, 2024). The present case examines a different disruption setting.

The chikungunya and Zika epidemics in French Guiana did not constitute a global pharmaceutical production disruption comparable to COVID-19. The analytical focus is therefore on downstream demand stress within an externally supplied and geographically constrained pharmaceutical chain. Keeping the network configuration common across the scenarios makes it possible to observe how changes in demand timing and therapeutic composition affect logistics performance without attributing the results to unobserved upstream production failures.

This distinction adds to epidemic supply chain research. Existing studies frequently examine large shocks affecting several network nodes and flows simultaneously. In the present study, a regional health event generates heterogeneous pharmaceutical demand profiles while external production is not modelled as disrupted. The results show that such demand-side shocks alone can generate materially different combinations of backlog, inventory pressure, and service performance.

The findings are also consistent with a time-dependent view of resilience in the literature, which distinguishes reference conditions, disruption response, adaptation, recovery, and persistent post-disruption states (Ivanov, 2022, 2024). In the present study, S0 defines the reference state, S1 and S2 represent two epidemic demand-shock states, and S3 represents an independent post-epidemic demand state. The experiment does not measure adaptation or a sequential recovery trajectory directly.

This point also clarifies the position of the findings within resilience theory. Recovery-oriented supply chain research indicates that a recovery trajectory cannot be inferred from independent scenario snapshots alone. It requires memory of prior system states and attention to logistics-system nervousness, because backlog, inventory depletion, and pipeline-stock imbalance may continue to disturb the network after the initial demand shock (Magableh & Mistarihi, 2024; Magableh et al., 2024). The present results therefore justify a recovery-oriented sequential extension, but they do not claim to measure recovery dynamics directly.

The results should not, however, be interpreted as evidence of long-term supply chain viability. Viability concerns the capacity of a supply chain to continue performing its function under

persistent or repeated environmental changes, whereas the present simulations examine a limited set of historically reconstructed demand states. The contribution remains principally within pharmaceutical supply chain resilience and stress-testing.

4.7.4 Research contribution

The study makes a methodological and an analytical contribution.

The methodological contribution lies in translating aggregated hospital pharmacy records into simulation-ready demand profiles without treating observed consumption as diagnosis-specific prescribing data. The procedure combines data-quality assessment, medical classification, phase-level positive differentials, epidemiological timing, and discrete-event simulation. Clinical reasoning determines which demand signals are plausible. Simulation then evaluates their logistics consequences. The two stages remain separate.

The analytical contribution concerns the interpretation of demand-driven resilience. The scenario comparison shows that a larger reconstructed demand input does not necessarily coincide with the lowest ELT service level or the largest backlog. The observed performance patterns are associated with concurrent differences in demand volume, temporal allocation, therapeutic composition, and exposure to the stock configuration. The experiment does not estimate the independent effect of each factor.

This observation is particularly relevant for healthcare supply chains because aggregate pharmaceutical volume does not preserve the therapeutic composition of demand. In the present experiments, lower aggregate demand can coexist with higher backlog when scenario timing, therapeutic composition, and stock exposure differ. These factors vary jointly, so the results are interpreted at scenario level rather than as evidence of a single class-specific causal effect.

Taken together, the results answer the three research questions. RQ1 is addressed through the reconstruction protocol that converts aggregated and non-uniform hospital records into clinically filtered and temporally distributed demand profiles. RQ2 is addressed through the four simulation scenarios, which show that these profiles produce distinct backlog, inventory, lead-time, and service-level responses under a common network structure and a consistently applied stock-setting rule. RQ3 is addressed by identifying inventory, monitoring, and post-epidemic management priorities that follow from the comparison, rather than by claiming that untested policies have already improved performance.

4.8 Managerial and practical implications

The findings suggest a three-phase decision structure for pharmaceutical supply chain management: State and Preparedness, Response, and Recovery and Adaptation. These phases are a managerial framing informed by the scenario comparison and the resilience literature; they are not sequential states measured directly by the present simulations. The experiments do not test the effectiveness of specific alternative inventory or transport policies.

4.8.1 State and Preparedness

The baseline operating state can first be characterised by therapeutic class rather than by aggregate pharmaceutical inventory alone. Stable performance in S0 does not establish that the same configuration would produce equivalent outputs under other epidemic-associated demand profiles. Baseline data can therefore serve as a reference for stress-testing alternative demand shapes before an emergency.

Inventory planning should reflect product-specific demand variability, replenishment lead time, storage constraints, shelf life, shortage criticality, and target service levels. The present results do not support prescribing a universal multi-month safety-stock rule. Such policies require separate, parameterised simulation experiments.

Data governance is equally important. Stable product coding, comparable extraction procedures, and regular pharmacy-consumption monitoring would make changes in therapeutic demand easier to detect. Epidemiological surveillance becomes operationally more useful when it can be connected to pharmaceutical consumption by therapeutic class.

4.8.2 Response

During an epidemic, decision-makers can monitor several logistics indicators simultaneously. Product backlog, backlogged orders, net inventory position, lead time, and ELT service level describe different aspects of simulated system performance. A relatively high service level should therefore be interpreted together with backlog and net inventory position rather than in isolation.

The scenario results also suggest examining the temporal and therapeutic structure of demand rather than aggregate volume alone. Class-specific monitoring can be used to compare where

and when demand concentration is associated with different model outputs, while avoiding attribution to a single factor unless that factor is tested separately.

Alternative emergency policies, including temporary inventory increases, sourcing adjustments, replenishment prioritisation, or transport changes, should be tested through separate simulation experiments before their operational effectiveness is claimed.

4.8.3 Recovery and Adaptation

The end of epidemic surveillance does not necessarily imply an immediate return to the baseline pharmaceutical demand structure. The independent 2017 scenario contains a positive differential relative to 2013 and generates the highest backlog and most negative net inventory position among the four experiments.

A practical implication is to continue post-epidemic monitoring of backlog, inventory position, and service indicators rather than assuming that the end of surveillance immediately restores the pre-epidemic demand pattern. This is particularly relevant for therapeutic classes whose observed consumption remains above the reference level.

Post-epidemic review can also inform future preparedness. Differences between expected and observed demand, product-specific backlog, and the timing of inventory pressure can be used to design new stress tests and to assess alternative replenishment policies in separate experiments.

4.9 Limitations and future research

The study has several limitations.

First, the hospital pharmacy records are aggregated and are not linked to diagnoses, patients, wards, or individual prescriptions. Positive differentials may therefore include consumption changes unrelated to Chikungunya or Zika. The reconstructed quantities must be interpreted as operational scenario inputs rather than causal estimates of disease-specific pharmaceutical use.

Second, product extraction was not uniform across years. In particular, a zero baseline for some therapeutic categories reflects the available extraction and cannot be interpreted as verified absence of clinical use.

Third, monthly baseline demand is estimated from annual 2013 quantities. This assumes a relatively stable distribution of routine demand within the reference year. The epidemic excess is then allocated over time according to epidemiological profiles rather than directly observed monthly diagnosis-linked dispensing.

Fourth, the temporal windows used for empirical reconstruction and simulation are not identical. The retained CHIKV differential is constructed from the combined annual 2014-2015 pharmacy records, while the primary simulated CHIKV horizon covers July 2014 to July 2015. Likewise, the Zika differential is calculated from the available 2016 annual extraction and then distributed over the January-September 2016 simulation horizon. These phase-level operational differentials are therefore not time-normalised estimates of epidemic-attributable consumption; they are scenario-construction inputs whose temporal placement is informed by the epidemiological curves.

Fifth, the model uses a finite-stock reference configuration and does not represent a fully parameterised dynamic replenishment policy. This design avoids introducing unsupported inventory rules, but backlog and inventory outputs should be interpreted as stress-test indicators rather than as an audit or exact reconstruction of historical pharmacy operations.

Sixth, formal parameter sensitivity analysis remains limited. Future work should systematically vary initial inventory, replenishment thresholds, supply lead times, demand concentration, and transport parameters to determine which assumptions have the strongest effect on backlog and service outcomes.

Seventh, the 2017 experiment represents an independent post-epidemic state rather than a sequential recovery trajectory. In Ivanov's ripple-effect perspective, this is a methodological limitation because the propagation of disruption can be observed only when the model preserves the state of the network across phases. The current model does not transfer final on-hand inventory by node, orders backlog, or pipeline inventory from the Zika scenario into the 2017 scenario. This independence assumption limits the capacity of the model to represent network memory, residual ripple effects, logistics-system nervousness, and time-to-recovery. A sequential simulation linking epidemic and post-epidemic states would allow disruption carry-over, recovery trajectory, and second-cycle rupture to be measured directly.

Eighth, the external supply chain model does not represent internal hospital distribution, community pharmacies, decentralised care facilities, product expiry, temperature-control constraints, supplier production limits, or patient-level treatment trajectories. Accordingly, the study does not assess internal practices at the Andrée Rosemon Hospital Center or decisions made by individual actors.

Future research should combine monthly diagnosis-linked dispensing data with more detailed logistics observations, including product-specific inventory levels, replenishment rules, transport lead-time distributions, and sourcing policies. Sequential simulations could then examine recovery trajectories rather than independent states.

Further experiments should also compare alternative inventory and replenishment policies, including class-specific safety stocks and lead-time-aware reorder rules. Sensitivity and policy experiments would allow the managerial priorities identified in this chapter to be converted into quantitatively tested resilience strategies.

Finally, the protocol could be applied to other geographically constrained healthcare systems and to other regional epidemics. Such studies would allow researchers to examine which findings are specific to French Guiana and which persist under different network structures, disease profiles, and replenishment conditions.

4.10 Conclusion

This chapter examines pharmaceutical supply chain performance under reconstructed chikungunya and Zika epidemic demand scenarios in French Guiana using a case-based discrete-event simulation approach. The analytical procedure starts from hospital pharmacy consumption records, applies clinical filtering, calculates positive phase-level differentials relative to the 2013 reference, and distributes the reconstructed additional demand according to the temporal profile of each epidemic before introducing it into AnyLogistix.

The simulation results reveal distinct performance patterns across the four scenarios. The baseline configuration generated no product backlog and maintained a positive net inventory position. The chikungunya scenario generated backlog while retaining a positive net inventory position and a high ELT service level. The Zika scenario generated a larger backlog, a negative net inventory position, and a lower ELT service level than the baseline and chikungunya scenarios. In the independent 2017 post-epidemic scenario, backlog increased further and the net inventory position remained negative, while the ELT service level was higher than in the Zika scenario.

The comparison shows that aggregate demand volume alone does not explain the differences observed across the simulation scenarios. The scenarios differ in demand magnitude, temporal distribution, and therapeutic composition, while the same stock-setting rule is applied across the comparative experiments. These conditions are associated with different combinations of backlog, inventory position, lead time, and ELT service level. The indicators should therefore be interpreted jointly when examining pharmaceutical supply chain performance under epidemic-related demand conditions.

The study also provides a traceable procedure for converting aggregated hospital pharmacy data into simulation inputs while maintaining a clear distinction between observed consumption, clinical classification, epidemiological timing, and simulated logistics outputs. The reconstructed demand quantities are not interpreted as disease-specific prescriptions or patient-level consumption. Similarly, the simulation outputs describe the behaviour of the model under the specified assumptions and configuration. They do not constitute an audit of historical logistics operations and do not support attribution of the observed simulation outcomes to specific organisations, decisions, or operational practices.

From a resilience perspective, the scenario comparison provides a structured way to examine supply chain behaviour across pre-epidemic, epidemic, and post-epidemic demand conditions. The stable baseline provides a reference configuration, while the epidemic scenarios show how different demand profiles are associated with different logistics outcomes under the same model structure. The independent 2017 scenario indicates that the reconstructed post-epidemic demand profile differs from the 2013 reference. Because the scenario is simulated independently, it should not be interpreted as a direct measurement of the recovery path from the 2016 Zika scenario.

Three methodological distinctions are central to the adjusted interpretation of the simulation results. First, cumulative backlog must be distinguished from time-normalised severity through the RST. Second, the AnyLogistix experiment must be distinguished from a real-time DSCT. Third, an independent post-epidemic state must be distinguished from a sequential recovery trajectory. Following Ivanov's ripple-effect logic, S3 should therefore be discussed as compatible with propagated residual disruption, but not as a direct measurement of the ripple effect because the model does not transfer S2 final states into S3. These distinctions clarify the two critical behaviours identified in S2 and S3: S2 shows how therapeutic-cluster structure can degrade service despite lower aggregate demand, while S3 shows how a post-epidemic condition can remain more severe after temporal normalisation and may correspond to a second-cycle disruption if network memory is modelled explicitly.

The contribution of the study lies in connecting clinically filtered empirical consumption data with discrete-event supply chain simulation in a setting where detailed diagnosis-linked and historical

logistics data are limited. This approach enables the examination of pharmaceutical demand scenarios while preserving a clear boundary between empirical observations and model-generated outcomes.

Future research should test alternative inventory and replenishment configurations through separate simulation experiments, examine the sensitivity of results to key model parameters, incorporate more detailed monthly and diagnosis-linked data where available, and develop sequential simulations capable of representing epidemic and post-epidemic trajectories within the same continuous model.

Chapter 5

Conclusions and Future works

5.1 Summary of Contributions

5.1.1 The Application of Artificial Intelligence Technologies in the Resilience and the Viability of Supply Chains: A Systematic Literature Review

In this chapter, we conducted a comprehensive systematic literature review of the role of artificial intelligence (AI) in strengthening supply chain resilience (SCR) and supply chain viability (SCV). By applying the structured TCCM (theory, context, characteristics, methodology) framework to 56 high-quality journal articles, we advanced both theoretical and practical understanding of AI's contributions to managing disruption risks.

The main contributions of this chapter were fourfold. First, we provided the most extensive synthesis to date of theories underpinning AI-enabled SCR/SCV, highlighting the predominance of dynamic capabilities theory, fuzzy set theory, organizational information processing theory, and transaction cost economics. Second, we offered a contextual analysis of industries, geographies, and risk types, showing that research has mainly focused on manufacturing, electronics, and food sectors, while health, economic, and environmental risks were the most widely studied. Third, we classified the antecedents, outcomes, and variables (independent, dependent, mediating, and moderating) used in empirical investigations, thereby mapping how AI adoption influences operational, strategic, and sustainability outcomes across SCs Fourth, we identified key methodological patterns in the literature, noting the prevalence of quantitative approaches and the relative scarcity of case studies and experimental research.

Beyond synthesizing the state of knowledge, this chapter highlighted critical research gaps and outlined future avenues. These included the investigation of advanced AI techniques (e.g., digital twins, reinforcement learning, generative AI), the examination of ethical and governance issues in AI-enabled SCs, the empirical evaluation of AI's role in adaptive reconfiguration under crisis conditions, and the quantification of the return on investment of AI applications for resilience and viability. By addressing these gaps, future studies could expand AI's transformative role in enhancing the adaptability, collaboration, and sustainability of global supply chains.

Overall, this chapter contributed by consolidating fragmented knowledge, proposing a structured research agenda, and offering actionable guidance for both scholars and practitioners seeking to harness AI for resilient and viable supply chain management in the Industry 5.0 era.

5.1.2 The Viability of Supply Chains with Interpretable Learning Systems: The Case of COVID-19 Vaccine Deliveries in France

In this chapter, we examined the role of interpretable learning systems, particularly artificial intelligence (AI) technologies, in enhancing supply chain resilience (SCR) and supply chain viability (SCV). Using the case of COVID-19 vaccine deliveries in France, we conducted an empirical descriptive study that demonstrated how AI-based learning systems can support effective decision-making during crises.

The contributions of this chapter were threefold. First, we developed and applied a generic model grounded in supervised, unsupervised, and semi-supervised learning techniques to predict vaccine deliveries and vaccination rates. This approach emphasized the importance of interpretability and explainability in AI-driven models, allowing stakeholders to understand the causal factors shaping predictions and ensuring the transparency required in high-stakes healthcare contexts. Second, we highlighted the practical implications of integrating interpretable learning systems into healthcare supply chains. Our findings demonstrated how such systems improved vaccine delivery planning, optimized resource allocation, supported prioritization strategies, and enhanced the traceability and security of vaccine stocks. Third, we contributed to theory by extending the literature on SCV and SCR with empirical evidence of AI's capacity not only to improve forecasting accuracy but also to strengthen explainability as a strategic asset in crisis management.

Beyond these contributions, this chapter identified key research gaps and future directions. We emphasized the need to investigate ethical concerns surrounding AI implementation in healthcare scs, including data quality, transparency, and public trust. We also called for further exploration of how interpretable learning systems could integrate socio-political factors such as lockdowns, public opinion, and compliance measures into predictive frameworks. Finally, we underlined the necessity of developing scalable, transferable models that could be adapted beyond the vaccine context to other healthcare crises and high-risk supply chains.

Overall, this chapter advanced both empirical and theoretical knowledge by demonstrating the added value of interpretable learning systems for managing uncertainty in healthcare scs. It showed how AI could serve not only as a predictive tool but also as a transparent and explainable decision-support mechanism, thereby reinforcing resilience, ensuring viability, and supporting equitable and sustainable vaccine distribution during global health crises.

5.1.3 Prediction Pharmaceutical Supply Chain Risks for Abroviral Epidemics: Insights from Chikungunya and Zika epidemics in French Guiana

In this chapter, we investigated the resilience of pharmaceutical supply chains (PSCs) during arboviral epidemics, focusing on the 2015–2016 outbreaks of Zika virus (ZIKV) and Chikungunya virus (CHIKV) in French Guiana. We employed a hybrid methodological framework that combined a real-world case study of Cayenne University Hospital Centre with a digital twin simulation model developed in Anylogistix. By integrating empirical data on drug consumption with structured assumptions about stock levels, inventory policies, and transportation flows, we analyzed the behavior of the PSC under epidemic-induced disruptions.

The contributions of this chapter were threefold. First, we provided one of the first empirical and simulation-based studies on PSC resilience in the context of arboviral diseases, a domain that has received limited scholarly attention compared to COVID-19. The results highlighted critical vulnerabilities in pharmaceutical logistics in French Guiana, including long lead times, recurrent stockouts, and last-mile delivery constraints caused by geographic and infrastructural limitations. Second, we developed and applied a structured resilience framework comprising three phases: Preparedness, Response, and Recovery/Adaptation. This framework offered actionable strategies such as scenario-based risk assessment, strategic stockpiling, diversification of supply networks, agile logistics, and digital transformation, providing practical guidance for policymakers, healthcare providers, and supply chain actors. Third, we contributed to theory by extending the discussion of PSC resilience beyond pandemic contexts, demonstrating how simulation-based digital twin models can serve as predictive tools for evaluating disruptions and testing adaptation strategies in resource-constrained epidemic-prone regions.

Beyond these contributions, the chapter identified several research gaps. The reliance on supplementary data necessitated making informed assumptions about stock availability and replenishment dynamics, underscoring the need for future studies to integrate data from wholesalers, hospitals, and pharmacies. Additionally, while our framework emphasized preparedness and recovery, future research should more deeply examine how emerging technologies—such as AI-enabled forecasting, blockchain traceability, and IoT monitoring—can operationalize resilience in pharmaceutical logistics. Comparative studies across regions with different epidemiological, infrastructural, and policy contexts would also help to validate

and generalize our findings.

Overall, this chapter advanced both academic and practical knowledge by illustrating how arboviral epidemics disrupt pharmaceutical supply chains and by proposing a scalable resilience framework to mitigate these impacts. It demonstrated that digital twin simulations, when combined with empirical insights, can provide robust tools for anticipating disruptions, supporting decision-making, and building viable and adaptive PSCs in the face of future health crises.

5.2 Limitations of the Proposed Approaches

This research acknowledges several limitations across the three approaches used—bibliometric, quantitative, and qualitative analyses—highlighting areas for further exploration. These limitations concern methodological choices, data availability, scope of application, and technological integration.

First, the reliance on retrospective datasets and publicly available reports represented a key constraint, particularly in the arboviral case study of French Guiana. The absence of comprehensive datasets on pharmaceutical stock levels, inventory management, and distribution flows necessitated the introduction of structured assumptions based on standard pharmaceutical practices. While these assumptions allowed us to construct a realistic simulation, they may not have fully captured the heterogeneity of real-world conditions, particularly in remote and resource-constrained settings. A more robust analysis would require direct access to data from wholesalers, pharmacies, and health institutions.

Second, the case-based methodology employed in Chapters 5 and 6—focusing, respectively, on COVID-19 vaccine deliveries in metropolitan France and on arboviral outbreaks in French Guiana—limited the generalizability of the findings. Although both contexts offered valuable empirical evidence, differences in governance structures, infrastructure, and supply chain maturity mean that results cannot be directly extrapolated to other regions without adaptation. Comparative and multi-country studies are needed to validate the proposed frameworks across diverse environments, including Sub-Saharan Africa, Southeast Asia, and the Mediterranean basin.

Third, the simulation models used in this research, while powerful in testing epidemic-induced disruptions, were subject to simplifications. The Anylogistix digital twin did not incorporate all potential dimensions of uncertainty, such as patient behavioral responses, informal supply

mechanisms, or black-market dynamics, which may substantially affect pharmaceutical availability during crises. Moreover, the models emphasized Preparedness, Response, and Recovery but paid less attention to the long-term evolutionary dynamics of supply chains and their capacity to adapt over successive crises.

Fourth, although the study highlighted the potential of AI and interpretable learning systems to enhance supply chain viability, the empirical application was constrained to a descriptive case of vaccine deliveries. Ethical and operational considerations—such as data privacy, algorithmic bias, and explainability—were only partially addressed. Furthermore, the proposed AI approaches were not implemented in real-time but were retrospectively applied to historical datasets, limiting insights into their practical deployment under the time pressures of ongoing crises.

Fifth**,** this work devoted less attention to the financial, regulatory, and socio-political dimensions of pharmaceutical supply chain resilience. For instance, procurement regulations, cross-border trade restrictions, and financial constraints faced by developing countries were not fully integrated into the simulation models. Similarly, the socio-political factors shaping epidemic responses, such as vaccine hesitancy or public trust in institutions, were beyond the scope of this research, yet remain crucial to the resilience and viability of healthcare supply chains.

Finally, the technological integration of advanced tools such as blockchain, iot, and AI-enabled forecasting was discussed conceptually but not empirically tested within the proposed frameworks. While the dissertation emphasized the importance of digitalization, the lack of operational implementation limited the ability to evaluate the feasibility, costs, and scalability of these technologies in real-world epidemic contexts.

5.3 Suggestions for Future Works

Future research in the aeronautical field could explore several avenues to build on the findings of this thesis. Expanding the sample size and incorporating diverse geographical contexts would offer a more comprehensive and representative view of AI adoption within the sector. Furthermore, conducting deeper analyses of specific variables, such as the effects of regulatory frameworks or the role of innovation management, could provide more detailed and actionable insights. Integrating quantitative methodologies alongside qualitative approaches would enhance the robustness of the findings, allowing for statistical validation of the relationships identified in this chapter. This multifaceted approach would not only address current limitations but also enrich the understanding of AI adoption, providing a more holistic perspective on its

organizational and industry-wide implications.

List of Abbreviations and Acronyms

AI Artificial Intelligence

ARA – Auvergne-Rhône-Alpes

ARCH – Andrée Rosemon Cayenne Hospital

CDPS – Centres Délocalisés de Prévention et de Soins

CHIKV – Chikungunya Virus

COVID-19 – Coronavirus Disease 2019

DSC – Digital Supply Chain

ELT – Expected Lead Time

FG – French Guiana

GS1 – Global Standards One (barcode standards)

IoT – Internet of Things

KPI – Key Performance Indicator

LT – Lead Time

NSAIDs – Non-Steroidal Anti-Inflammatory Drugs

RQ – Research Question

SC – Supply Chain

SCM – Supply Chain Management

SCR – Supply Chain Resilience

SCRM – Supply Chain Risk Management

SIRM – Susceptible-Immune-Infected-Recovered Model

SPG – Société Pharmaceutique Guyanaise

UCD – Unité Commune de Dispensation (Common Dispensing Unit)

XAI – Explainable Artificial Intelligence

ZIKV – Zika Virus

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Appendix

Appendix to "The Application of Artificial Intelligence Technologies in the Resilience and the Viability of Supply Chains: A Systematic Literature Review"

Appendix Content

1. Detailed results of the main theories identified in the selected studies: Theoretical and methodological approaches
2. Main contexts of the studies: industries, countries of origin and areas of risks covered in the research
3. Main characteristics of the studies: antecedents and outcomes investigated the research
4. The main methodologies identified in the studied

1.1.1. Detailed results of the main theories identified in the selected studies

Table A1: Theoretical Approaches Used in the Selected Studies

Theories	No. Of articles	%	Exemplary studies	Theory definition	Ref.	Application to AI in SCV/SCR	Potentiel Future Research Directions
No Guiding Theory	26	42%	(Chien et al., 2020); (Rabelo et al., 2008); (Chi et al., 2007); (Mariappan et al., 2022); (Deiva et al., 2022); (Zamiela et al., 2022); (Xu et al., 2023); (Zaoui et al., 2023); (Roux et al., 2023); (Sadeghi R. et al., 2024); (Gupta et al., 2023); (Le et al., 2023); (Dubey et al., 2022); (Jauhar et al., 2023); (Leoni et al., 2022); (Rafi-Ul-Shan et al., 2024); (Yadav et al., 2024); (Wang et al., 2023); (Sharma 2023); (Ivanov 2023); (Song et al., 2024); (Brintrup et al., 2024)				
OIPT	3	5%	(Gupta et al., 2021); (Belhadi et al., 2021); (Behl et al., 2022)	Is a theoretical framework that examines how organizations process and utilize information to make decisions and solve problems. OIPT emphasizes the role of uncertainty and the need for information processing in organizational design and decision-making processes. It suggests that organizations can reduce uncertainty by creating slack resources, self-contained tasks, investing in information systems, and establishing lateral relations.	(Ochoa, 2022)	Explains how AI reduces information-processing gaps, enhances decision quality and reduces coordination costs.	Examine AI as an enabler of adaptive information structures in highly uncertain SC environments.
Causal Theory	2	3%	(Lin et al., 2022); (Kazancoglu et al., 2022)	Causal decision theory is a general theory of rational decisions that focuses on the causal features of decision problems.	(Armendt, 2018)	Helps AI model causal links between disruptions and supply outcomes for proactive planning	Use causal AI to enhance counterfactual reasoning and improve disruption impact forecasting.
Transaction Cost	2	3%	(Bechtsis et al., 2022); (Kazancoglu et al., 2022)	Transaction cost theory is a theory that explains how firms	(Mooi, 2015)	AI automates contracting, monitoring, and	Explore AI in smart contracts and decentralized

Economics Theory				organize transactions and choose a form of governance that minimizes production and transaction costs.		enforcement, reducing transaction frictions.	governance across complex global SCs.
Resource-based View Theory	2	3%	(Effah et al., 2023); (Dey et al., 2023)	The resource-based view theory provides a framework to evaluate the strategic fit of resources from China in developing countries.	(Kshetri, 2008)	Frames AI as a strategic capability for resilience and viability through data-driven insights	Investigate how AI capabilities act as VRIN :
				It originated from Birger Wernerfelt (1984) and was further developed by Jay B. Barney (1991) and other scholars.			· Valuable: AI enables fast decision-making and disruption prediction.
				Competitive advantage is determined by a firm's resources and capabilities.			· Rare: Few firms have highly customized, fully integrated AI in supply chains.
				These resources protect the firm from competition, differentiate its products, and lead to superior profits and performance.			· Inimitable: AI models trained on proprietary data + years of process knowledge are hard to copy.
							· Non-substitutable: Human decision-making or simpler software might not deliver the same speed/accuracy.
A Learning Process Theory	1	2%	(Cavalcante et al., 2019)	Learning theory seeks to explain how individuals acquire, process, retain, and recall knowledge during the process of learning. Environmental, cognitive, and emotional influences, along with prior experiences, play a vital role in comprehending, acquiring, and retaining skills or knowledge. Motivation plays an important role in enabling the process of learning and is said to be the driving force	(De Houwer et al., 2013)	Explains how AI systems support organizational learning through real-time feedback and adaptation.	Model SC learning loops using reinforcement learning or continual learning in AI.

				where activity is started and sustained to achieve a target.			
Complexity Theory Approach	1	2%	(Gružauskas et al., 2019)	It explains how the relationships between members of these systems give rise to collective behavior and shed light on how a system interacts with its environment. It does not need to have a complex explanation.	(Sammut-Bonnici, 2015)	Justifies AI for managing non-linear, interconnected SC networks under uncertainty.	Develop complexity-aware AI that adapts to evolving SC network behaviors
Innovation Adoption Theory	1	2%	(Wong et al., 2020)	Innovation adoption theory is an idea, practice or object that is perceived as new by an individual or other unit of adoption.	(Zoellner et al., 2017)	Explains adoption patterns of AI in SC settings	Study barriers and accelerators to AI adoption across SC contexts
Social Exchange Theory	1	2%	(Chen et al., 2022)	Social exchange theory (SET) was defined by Blau (1964) and Emerson (1976) as an action-reaction system of exchange based on reward mechanisms for value exchange. SET considers direct social interactions between actors through four elements: trust, commitment, reciprocity, and power.	(Benitez et al., 2022)	AI enables trust-based coordination and partner selection through predictive collaboration tools.	Model trust dynamics in AI-supported SC partnerships (e.g., via explainable AI)
The Proximity Index Value	1	2%	(Zamiela et al., 2022)	A proximity index (PX) inspired by island biogeography theory is described which quantifies the spatial context of a habitat patch about its neighbors. The index distinguishes sparse distributions of small habitat patches from clusters of large patches.	(Gustafson et al., 1994)	AI uses proximity metrics for location optimization and risk analysis.	Explore spatial AI to enhance SC network viability under regional disruptions.
Theory of Customer Preference	1	2%	(Chiu et al., 2016)	The theory of customer preference is used to determine the impact of observable demands for commodities of	(Barten et al., 1982)	AI models customer demand fluctuations to align SC capabilities and improve viability.	Use AI to simulate behavioral preferences under disruption and

				alternative assumptions on the objectives, the behavioral rules of the consumer, and the constraints that they face while making a decision.			redesign customer-centric SCs.
Practice-based View	1	2%	(Chien et al., 2023)	The practice-based view (PBV) theory, proposed by Bromiley and Rau in 2014, emphasizes that an organization's competitive advantage stems not only from its knowledge but also from its operational procedures. PBV aims to elucidate the reasons behind variations in organizational performance in response to widely available practices that are not unique or incomparable.	(Bromiley et al., 2014)	AI helps replicate high-performing SC practices across sites through data analytics.	Explore how AI democratizes access to best practices, improving resilience system-wide.
Probability Theory / Bayesian Approach	1	2%	(Ahmed et al., 2023)	Bayesian law expresses the relationship between dependent variables. The Bayesian relation uses a numerical estimate of the probabilistic knowledge of the hypothesis before the observations occur and provides a numerical estimate of the probabilistic knowledge of the hypothesis after the observations.	(Witten et al., 2017)	Supports AI reasoning under uncertainty through probabilistic inference.	Advance adaptive Bayesian networks for real-time SC decision support under dynamic risks
Inverse Data Envelopment Analysis (IDEA)	1	2%	(Lin et al., 2024)	Inverse data envelopment analysis (DEA) is a mathematical programing approach that focuses on determining the optimal quantity of inputs and/or outputs for each decision-making unit under input and/or output perturbations to achieve a specific efficiency target.	(Emrouzneja d et al., 2023)	AI applies IDEA for performance benchmarking and resilience target setting.	Integrate IDEA personalized SC improvement paths under resource constraints.

Table A2: Methodological Approaches Used in the Selected Studies

Methodological Approaches	No. of articles	%	Exemplary studies	Theory definition
Dynamic Capability Theory (DCT)	5	8%	(Cuong et al., 2022); (Li et al., n.d.); (Tian et al., 2024); (Singh et al., 2024)	Dynamic Capabilities are the firm's ability to integrate, build, and reconfigure internal and external resources/competences to address and shape rapidly changing business environments.
Fuzzy Set Theory	4	6%	(Wu et al., 2020); (Hosseini et al., 2019); (Balaman et al., 2018); (Jiang et al., 2023)	Fuzzy set theory is a mathematical framework that allows for the representation and manipulation of uncertainty and vagueness in data and decision-making processes. It extends classical set theory by introducing the concept of fuzzy sets, which are sets with elements that have degrees of membership rather than being strictly binary.
Data-Driven Robust Optimization Approach	2	3%	(Gumte et al., 2021); (Byeongmok et al., 2024)	It is a popular approach to optimization under uncertainty. The key idea is to define an uncertainty set of realizations of the uncertain parameters and then optimize against worst-case realizations within this set.
Differential Sampling Rate Theory	1	2%	(Yao et al., 2022)	The sampling theorem essentially says that a signal must be sampled at least twice the frequency of the original signal. Since signals and their respective speeds can be easily expressed by frequencies, most explanations of artifacts are based on their representation in the frequency domain.
Graph Theory	1	2%	(Bottani et al., 2019)	Graph theory provides us with the means to analyze these graphs focusing on their structural components and corresponding properties. Several common techniques for network analysis are described in the following: centrality analysis is used to identify the most central entities in your network.

Rough Set Theory + Wavelet Theory	1	2%	(Belhadi et al., 2022)	Rough set theory can be used for classification to discover structural relationships within imprecise or noisy data. It applies to discrete-valued attributes. Continuous-valued attributes must, therefore, be discretized before their use.
Rule-Based Deduction	1	2%	(Shokouhyar et al., 2019)	Rule-based systems provide the computational mechanisms found in most expert systems. Knowledge is specified via facts and IF-THEN rules, and *modus ponens* is used as the underlying inference method to derive new conclusions from existing knowledge.
Prescriptive Analytics-based	1	2%	(Ivanov 2024)	Prescriptive analytics refers to a type of analytics that focuses on recommending actions to achieve desired outcomes by utilizing various data analysis techniques.
				This approach goes beyond descriptive and predictive analytics by not only predicting future outcomes but also suggesting the best course of action to optimize those outcomes.
Probability Theory / Bayesian Approach	1	2%	(Ahmed et al., 2023)	Bayesian law expresses the relationship between dependent variables. The Bayesian relation uses a numerical estimate of the probabilistic knowledge of the hypothesis before the observations occur and provides a numerical estimate of the probabilistic knowledge of the hypothesis after the observations.
Inverse Data Envelopment Analysis (IDEA)	1	2%	(Lin et al., 2024)	Inverse data envelopment analysis (DEA) is a mathematical programing approach that focuses on determining the optimal quantity of inputs and/or outputs for each decision-making unit under input and/or output perturbations to achieve a specific efficiency target.

1.1.2. Main contexts of the studies: industries, countries of origin and areas of risks covered in the research

Table A3: Industries examined in the research on the application of AI technologies in the management of SC disruptions

Industry	NB of articles	%	Exemplary study
Not stated	15	27%	(Le and Behl 2023); (Ivanov 2023); (Yu et al. 2022) ;(R. K. Singh, Modgil, and Shore 2024);(Shivam Gupta et al. 2023);(Sadeghi R. et al. 2024);(Roux et al. 2023);(Wong et al. 2020) ; (Behl et al. 2022) ; (S. Singh et al. 2019) ; (Bechtsis et al. 2022) ; (A Belhadi et al. 2021) ; (Yao et al. 2022) ;(Dun Li and Bangdong Zhi and Tobias Schoenherr and Xiaojun Wang, n.d.) (Xu et al. 2023)
Manufacturing Industry	12	21%	(Alexandra Brintrup Edward Kosasih and MacCarthy 2024) ;(Cavalcante et al. 2019) ;(Wong et al. 2020) ;(Behl et al. 2022) ;(Amine Belhadi et al. 2021) ;(Chiu and Lin 2016) ;(S Hosseini and Khaled 2019) ;(Jiang, Feng, and Huang 2023) ;(Leoni et al. 2022) ;(Tian et al. 2024) ;(Byeongmok Kim and Lee 2024) ;(Prasanta Kumar Dey Soumyadeb Chowdhury and Sarkar 2023)
Electronical	5	9%	(Fu and Chien 2019); (Wu et al. 2020); (Rabelo et al. 2008); (C.-F. Chien, Lin, and Lin 2020); (Fu and Chien 2019)
Food	4	7%	(Effah et al. 2023);(Lin and Ma, 2022); (Gružauskas, Gimžauskienė, and Navickas 2019) ; (Bottani et al. 2019)
Pharmaceutical & Healthcare	4	7%	(Modgil et al. 2022) ; (Mariappan et al. 2022) (Zaoui et al. 2023)(Yadav and Singh 2024)
Energy	3	5%	(Gumte et al. 2021) ; (Ş Y Balaman et al. 2016) (Wang et al. 2023)
Digital	2	4%	(Cavalcante et al. 2019) ; (S.-W. Lin and Lu 2024)
SC	2	4%	(Ivanov 2024) ;(Sharma 2023)
Nongovernmental organizations (NGOs)	2	4%	(Dubey et al. 2022); (Chen-Fu Chien, Ku, and Lu 2023)
Fashion	2	4%	(Ahmed et al. 2023) ;(Rafi-Ul-Shan et al. 2024)
Automotive	1	2%	(Kazancoglu et al. 2022)
IT	1	2%	(S Gupta et al. 2021)
Maritime	1	2%	(Cuong et al. 2022)
Services	1	2%	(Shokouhyar et al. 2019)
Industrial Automation	1	2%	(Chen, Biswas, and Talukder 2022)
Confidential	1	2%	(Chi et al. 2007)
Retail industry	1	2%	(Jauhar et al. 2023)
Energy	1	2%	(Song et al. 2024)

Table A4: Countries of origin in the research on the application of AI technologies in the management of SC disruptions

Country	No. Of articles	%	Exemplary studies
South-East Asia (Vietnam, Malaysia, India)	7	12,50%	(Cuong *et al.*, 2022);(Wong *et al.*, 2020);(Mariappan *et al.*, 2022);(Behl *et al.*, 2022);(Dey *et al.*, 2023);(Ahmed *et al.*, 2023);(Lin and Lu, 2024)
East Asia (China, Taiwan)	6	10,71%	(Wong *et al.*, 2020) ;(Yao *et al.*, 2022);(Wu *et al.*, 2020);(Chien, Lin and Lin, 2020);(Yu *et al.*, 2022);(Tian *et al.*, 2024)

North America (US)	4	7,14%	(Hosseini and Khaled, 2019);(Gupta *et al.*, 2021) ;(Christian Zamiela, Hossain and Jaradat, 2022);(Byeongmok Kim and Lee, 2024)
Europe (France, UK…)	5	7,14%	(Lin and Ma, 2022);(Balaman *et al.*, 2018);(Rafi-Ul-Shan *et al.*, 2024);(Alexandra Brintrup Edward Kosasih and MacCarthy, 2024);(Zaoui *et al.*, 2023)
Country not reported	34	62,50%	(Cavalcante *et al.*, 2019);(Kazancoglu *et al.*, 2022);(Gružauskas, Gimžauskienė and Navickas, 2019);(Gumte *et al.*, 2021);(Fu and Chien, 2019);(Yadav and Singh, 2024);(Wang *et al.*, 2023);(Effah *et al.*, 2023);(Song *et al.*, 2024);(Ivanov, 2023b);(Jauhar *et al.*, 2023);(Dubey *et al.*, 2022);(Le and Behl, 2023);(Gupta *et al.*, 2023);(Sadeghi R. *et al.*, 2024);(Roux *et al.*, 2023);(Leoni *et al.*, 2022);(Chien, Ku and Lu, 2023);(Jauhar *et al.*, 2023);(Jiang, Feng and Huang, 2023);(Roux *et al.*, 2023);(Xu *et al.*, 2023);(Dun Li and Bangdong Zhi and Tobias Schoenherr and Xiaojun Wang, no date);(Ivanov, 2024a);(Sadeghi R. *et al.*, 2024)

Table A5: Areas of risk covered in the research on the application of AI technologies in the management of SC disruptions

Type of risk	Risk	No. Of articles	%	Exemplary studies	Risk impact to SCR and SCV
Healthcare	COVID-19	19	33%	(Behl et al. 2022); (Cuong et al. 2022); (Zamiela et al., 2022); (Ganesh et al.,2022); (Mariappan et al. 2022); (Kazancoglu et al. 2022); (Bechtsis et al. 2022) ;(Ivanov 2024); (Li et al., 2023); (Xu et al. 2023) ; (Zaoui et al. 2023) ; (Jiang et al., 2023) ; (Brintrup et al., 2024) ; (Tian et al. 2024); (Yadav et al., 2024); (Ahmed et al., 2023); (R. K. Singh et al., 2024); (Ivanov 2023); (A. Sharma 2023)	Healthcare risks impact SCV due to the criticality of delivery, perishability, and regulatory pressure. AI enhances SCR by enabling real-time monitoring, predictive planning, and adaptive logistics to maintain service continuity.
Economic	Growing urbanization, consumer demand for organic products, and e-commerce growth	13	23%	(Chen et al., 2022); (Gumte et al., 2021);(Wu et al., 2020); (Chien et al., 2020); (Gružauskas et al., 2019); (Cavalcante et al., 2019); (Fu & Chien, 2019); (Bottani et al., 2019); (Shokouhyar et al., 2019); (Chiu & Lin, 2016); (Rabelo et al., 2008); (Jauhar et al., 2023); (Rafi-Ul-Shan et al., 2024)	Economic shifts affect SCV through price volatility, demand-supply mismatch, and global competition. AI supports SCR by enabling adaptive sourcing, economic forecasting, and dynamic decision-making.
	Insurance coverage and contract necessity				
	Market dynamics, information integration, and quick response challenges				
	Risks of oversupply and shortage of key components				
	A customer-driven economy				
	Impact of global economic developments				
	Highly competitive market conditions				
	Uncertainties caused by both internal and external influences				
	Complex export processes and sustainability demands				

Technological	Data-intensive environments The explosive rise in technologies	5	9%	(Wong et al. 2020); (Chi et al. 2007) ; (Sadeghi R. et al. 2024) ; (Dubey et al. 2022); (Chien et al., 2023)	Technology-related risks threaten SCV via system dependency and cybersecurity exposure. AI boosts SCR through automation, anomaly detection, and robust digital infrastructures.
Environmental	Extreme weather events Environmental sustainability aspects	4	7%	(Lin et al., 2022); (Hosseini et al., 2019); (Effah et al., 2023); (Lin et al., 2024)	Environmental risks undermine SCV by disrupting operations and increasing compliance burdens. AI improves SCR by enabling weather forecasting, carbon tracking, and sustainability modeling.
Financial	Bankruptcy and credit crises	2	4%	(Yao et al. 2022); (Gupta et al., 2023)	Financial instability affects SCV by limiting liquidity and investment capacity. AI strengthens SCR via financial risk modeling, cost optimization, and scenario simulation.
Environmental & Economic		1	2%	(Ş Y Balaman et al. 2016)	Joint environmental-economic risks reduce SCV by increasing uncertainty and cost pressures. AI supports SCR by helping balance efficiency and sustainability in decision-making.
Other	Disruptive situations Numerous types of disruptions and failures such as fire, storm, machine failure The dynamism and uncertainty of the SC	13	23%	(Song et al. 2024); (Dey et al., 2023); (Kim et al., 2024); (Le et al, 2023); (Wang et al. 2023); (Leoni et al. 2022); (Belhadi et al., 2022); (Gupta et al., 2021); (S. Singh et al., 2019); (Schätter et al. 2019); (Roux et al. 2023)	

1.1.3. Main characteristics of the studies: Antecedents and outcomes investigated the research

Here, we identify the main characteristics and variables of influence and examine the antecedents and outcomes that shape the implementation of AI technologies, highlighting factors like partner selection and data-driven decision-making that contribute to improved SC performance, efficiency, adaptability, risk management, innovation, and collaboration. The variables are categorized into independent, dependent, moderating, and mediating variables, with examples such as sales data, market demand, and production expenses. Understanding these characteristics is essential for designing resilient and viable SCs.

Table A6: Overview of antecedents and outcomes investigated in reviews of AI applications to improve SCR and SCV research

Antecedents	Outcomes	Relation to SCV and SCR
Need for effective analysis methods to understand and improve SC behavior (Cuong et al., 2022)	SC resilience	Supports SCR by enabling adaptive capacity and informed response to disruptions.
Increased availability of data and computing power enables more sophisticated forecasting methods (H. Han et al., 2022) Recognition of the need for collaboration among multiple stakeholders to achieve sustainability (Sindhwani et al., 2022)	SC sustainability	· Enhances SCV by improving planning accuracy and SCR through scenario-based modeling. · Strengthens both SCV and SCR by fostering coordinated risk management and long-term alignment.
Increased awareness and concern for sustainability issues in SC management (Wu et al., 2020)	SC efficiency	Improves SCV by reducing waste and supporting regulatory compliance.
Need for effective partner selection strategies in sustainable SCs (Wu et al., 2020)	SC performance	Impacts SCV via strategic alignment and SCR through partner reliability during disruption.
Need to improve productivity on construction sites and the limitations of existing methods for predicting concrete-pouring duration (Maghrebi et al., 2016)	SC adaptability	Supports SCR by enabling flexibility and operational responsiveness.
Need for accurate credit risk prediction to aid effective decision-making in enterprises (Yao et al., 2022)	SC optimization	Affects SCV by reducing financial exposure and improving investment decisions.
Growing importance of data-driven decision-making in SC management (Baryannis et al., 2019)	SC innovation	Drives SCV through smarter operations and enhances SCR by enabling proactive risk response.
Increasing need for resilient and sustainable SCs in the face of disruptions and environmental concerns (Shokouhyar et al., 2019)	SC collaboration	Reinforces both SCV and SCR through joint preparedness and knowledge sharing.
Growing awareness of social and environmental concerns in SCs (Paraschos et al., 2022)	SC transparency	Enhances SCV through adherence and consumer confidence.

Table A7: Variable types examined in the research

Variable Type	Examples
Independent Variables	Availability of resources Historical sales data (number of units sold per day)

	Time
	Inflation rate
	Market demand
	Ambient temperature
	Atmospheric pressure
	Humidity
	Port capacity
	Range of typical storage temperatures for products
	Storage temperature
	Temperature range specified in relevant regulations.
	Traffic patterns
	Temperature, precipitation, and solar radiation
	Supplier selection process
	Market demand
Mediating Variables	Market prices, subsidies, and production costs
	Role of multiple stakeholders
	Climate conditions
	Decision-making processes, competitive advantage
	Absorptive capacity and technology dependency
	Information complexity (IC)
	Knowledge management processes (KMPs)
vModerating Variables	Port location
	Location, FC code, FC city of location,
	Therapeutic Supply Logistics provider identification number, and mode of payment for the transaction by the patient
	Firm age
	Industry sector
	Supplier type
	Buyer type
	Country/region
	Governance structure
	Employee skills and competencies
Dependent Variables	Availability of biowaste
	Forecasted demand (number of units to be sold in the future)
	Lead time, total cost, order fulfillment rate, and waste rate of the SC Configuration for a personalized product

	Production rate
	Total cost of tardiness
	Total profit
	Speed and temperature setting of the truck
	Storage temperature
	Temperature of the cargo inside the container
	Volume of cargo
	The arrival time
	Productivity
	Critical success factor
	User satisfaction
	Decision support methodology

Table A8: Independent variables investigated in the research

Independent variables
Economic
Historical sales data (number of units sold per day) Time (days)
Assets, liabilities, and cash flow
Control parameters such as cost and implementation time
Evaluation criteria used to assess potential partners' sustainability performance
Execution and decision activities, resources, flows between activities, and partners
Inflation rate
Market demand
Availability of resources
Production quantity and inventory replenishment
Environmental
Atmospheric pressure
Ambient temperature
Wind speed
Humidity
Temperature, precipitation, and solar radiation
Logistic
Type of transportation medium
Type of product being transported
Traffic patterns
Port capacity
Departure and destination ports for each shipping company
Maximum number of days between the arrival of different portions of an offer.
Storage temperature
Range of typical storage temperatures for products
Level of refrigeration of the truck
Temperature range specified in relevant regulations
Other
Channel demand
Construction site parameters
Level of human involvement in technology

Manufacturing process type
Number of farms/products
Shipping companies offer
Supplier selection process
Shipping companies offer
Technological
Deep RL algorithm
Social media data
Various Machine Learning (ML) classifier models are used to predict shipment times
AI and XAI
Datafication technologies
Data collection, and analytics methods.
Big data analytics capability (technical skills, managerial skills, data-driven decision culture)
AI-BDAC
Healthcare
Records of therapeutic shipments collected pre-COVID lockdown and post-COVID lockdown
Severity of a disaster

Table A9: Dependent variables investigated in the research

Dependent variables
Economic
Activity cost, execution time of an activity
Credit score, probability of default, and credit limit
Forecasted demand (number of units to be sold in the future)
Lead time, total cost, order fulfillment rate, and waste rate of the SC configuration for a personalized product
Production rate
Productivity
Inventory balance point and sales increase
Total cost of tardiness
Total profit over
Decision support methodology
Improved risk management, cost savings, strategic decision-making
Logistic
Logistics clusters activities in the food industry.
Speed and temperature setting of the truck
Storage temperature depends on the range of typical storage temperatures for products, the level of refrigeration of the truck, and the temperature range specified in relevant regulations.
Temperature of the cargo inside the container
The volume of cargo (in number of containers), The arrival time of the last portion of an order, transportation cost for the carriage of the containers from the destination port to the destination city by truck
Healthcare
Frequency of occurrence of a pandemic event
Shipment times of therapeutic supplies
Environmental
Risk magnitude
Temperature
CO2 reduction strategies
Other
Availability of Bio-Waste
Fluctuations in finished goods inventory and actual capacity relative to desired capacity

Critical success factor theory
Partner classification: strategic partner, preference partner, leverage partner, and routine partner
Maximum assembly completion time
User satisfaction

Table A10: Moderating variables investigated in the research.

Articles	Moderating Variables
(Cavalcante et al., 2019)	Market prices, subsidies, and production costs
(Gumte et al., 2021)	The role of multiple stakeholders
(Ivanov, 2024)	Risks of product shortages and inflation.
(Xu et al., 2023)	Decision-making processes, competitive advantage.
(Sadeghi et al., 2024)	Absorptive capacity and technology dependency
(Gupta et al., 2023)	Environmental dynamism is identified as a moderating variable influencing the relationship between AI, blockchain technology, and financial resilience in SCs
(Dubey et al., 2022)	IC
(Effah et al., 2023)	Specific data requirements for AI algorithms.
(Wang et al., 2023)	Sustainable performance of material suppliers and the selection of the most suitable supplier based on the proposed methodology
(Singh et al., 2024)	Degree of transparency
(Lin and Lu, 2024)	Environmental regulations, geographical risks.
(Dey et al., 2023)	Employee skills and competencies

Table A11: Mediating variables examined in the research.

Articles	Mediating variables
(Zhao et al., 2021)	Port location
(Mariappan et al., 2022)	Location, therapeutic supply logistics provider identification number, and mode of payment for the transaction by the patient
(Cavalcante et al., 2019)	Market prices, subsidies, and production costs
(Gumte et al., 2021)	Role of multiple stakeholders
(Wong et al., 2020)	Climate conditions
(Belhadi et al., 2021)	Firm age, industry sector, supplier type, buyer type, country/region
(Jiang et al., 2024)	Corporate attributes (age, size, ownership, industry types), internal discretionary resources, managerial roles, and external business environment factors
(Dey et al., 2023)	Sustainable practices, SC agility, risk management.
(Singh et al., 2024)	Transparency, disruption impact, mass customization of procurement strategy.
(Belhadi et al., 2022)	Time
(Ivanov, 2024)	Prescriptive analytics, network optimization.
(Brintrup et al., 2024)	KMPs
(Tian et al., 2024)	SC resilience
(Chien et al., 2023)	IC was found to mediate the relationship between agility, resilience, and performance in the humanitarian SC
(Sadeghi et al., 2024)	AI transparency and agile decision-making
(Dubey et al., 2022)	IC
(Ivanov, 2023)	Human decision-making rules, AI algorithms.
(Xu et al., 2023)	Risk mitigation procedures
(Effah et al., 2023)	Organizational resources and risk governance framework
(Lin and Lu, 2024)	Economic indicators like earnings persistence and market recognition
(Yu et al., 2022)	Emerging IT capability

1.1.4. The main methodologies identified in the studies

Table A12: Main methodologies identified in the study.

Ord	Paper Title	Approach	Type
1	(Hosseini and Khaled, 2019)	Identification of resilience criteria, data mining, predictive analytics models, ensemble methods, and AHP	Quantitative
2	(Mariappan et al., 2022)	Data collection, preprocessing, feature engineering, machine learning model-building, cross-validation, and performance evaluation	Quantitative
3	(Cavalcante et al., 2019)	Development and application of a machine learning-based simulation model	Quantitative
4	(Gumte et al., 2021)	Development of a robust SC model, fuzzy clustering, techno-economic and environmental analysis	Qualitative and quantitative
5	(Gupta et al., 2021)	Semi-structured interviews, thematic analysis	Qualitative
6	(Belhadi et al., 2021)	Conceptualization, survey data collection, structural equation modeling	Qualitative and quantitative
7	(Belhadi et al., 2022)	MCDM techniques, AI-based algorithms	Quantitative
8	(Bechtsis et al., 2022)	Analysis of existing frameworks, proposal of a generalized data-sharing and monetization framework	Qualitative and quantitative
9	(Chien et al., 2020)	UNISON framework based on deep reinforcement learning	Quantitative
10	(Lin and Ma, 2022)	Anomaly detection algorithms, change point analysis, spike analysis	Quantitative
11	(Zamiela et al., 2022b)	Case study	Quantitative
12	(Singh et al., 2019)	Ontology-based decision support system, mixed integer linear programming, hybrid particle swarm optimization-differential evolution	Quantitative

13	(Yao et al., 2022)	Decision tree ensemble model, differential sampling rate, synthetic minority oversampling technique, AdaBoost	Quantitative
14	(Gruzauskas et al., 2019)	Agent-based model, machine learning algorithms, forecasting, market fluctuations	Quantitative
15	(Shokouhyar et al., 2019)	Fuzzy expert system, information technology SC	Qualitative
16	(Balaman et al., 2018)	Bi-level decision support system, fuzzy ε-constraint method, biomass-based SCs	Quantitative
17	(Chi et al., 2007)	Machine learning algorithms, genetic algorithms, vendor-managed replenishment system	Quantitative
18	(Wu et al., 2020)	Fuzzy ensemble learning model, partner qualification and classification, partner evaluation process	Quantitative
19	(Bottani et al., 2019)	Bi-objective mixed integer programming, ant colony optimization algorithm	Quantitative
20	(Behl et al., 2022)	Multi-theoretical approach, Big Data analytics capabilities, MSME service firms	Qualitative
21	(Cuong et al., 2022)	Nonlinear analysis methods, fractional calculus, MCDM strategies	Quantitative
22	(Chiu and Lim, 2016)	Simulation techniques, optimization models, decision theory	Quantitative
23	(Deiva Ganesh and Kalpana, 2022)	Ontology-based decision support system, mixed integer linear programming, particle swarm optimization	Quantitative
24	(Chen et al., 2022)	Cooperative water wave optimization algorithm	Quantitative
25	(Wong et al., 2020)	Simulation-based approach	Quantitative

26	(Hu et al., 2019)	Temporal aggregation, machine learning technologies, empirical study	Quantitative
27	(Kazancoglu et al., 2022)	DEMATEL method	Quantitative
28	(Rabelo et al., 2008)	System dynamics simulation, neural networks, Eigenvalue analysis	Quantitative
29	(Ivanov, 2024)	Assessing SC resilience during the pandemic, considering recovery strategies, and predicting adverse effects	Qualitative
30	(Li et al., 2023)	Classifying 1717 papers in SC resilience using machine learning thematic clustering	Quantitative
31	(Xu et al., 2023)	Intelligent SC risk prediction system using AI for risk identification and mitigation	Quantitative
32	(Zaoui et al., 2023)	Prescriptive analytics for optimizing actions during COVID-19	Quantitative
33	(Roux et al., 2023)	Organizational support model tested on Vietnamese SME managers	Quantitative
34	(Sadeghi et al., 2024)	Experimental design to test a research model	Quantitative
35	(Gupta et al., 2023)	Mixed-method design to test hypotheses	Qualitative and Quantitative
36	(Le and Behl, 2023)	Qualitative approach on AI adoption's impact on SC sustainability	Qualitative
37	(Dubey et al., 2022)	Two-stage mixed-method: interviews + cross-sectional survey	Qualitative and Quantitative
38	(Jiang et al., 2024)	Fuzzy set QCA to explore configurations for reactive SC resilience	Qualitative
39	(Jauhar et al., 2023)	Evolutionary computation, genetic algorithms, Bayesian regression for SC performance and employee well-being	Quantitative

40	(Chien et al., 2023)	Qualitative classification for spare parts	Qualitative
41	(Leoni et al., 2022)	Partial least squares SEM with Italian manufacturing executives	Quantitative
42	(Brintrup et al., 2024)	Logistic regression on SC and automation in UK companies	Quantitative
43	(Rafi-Ul-Shan et al., 2024)	Fuzzy group AHP and FMEA for risk analysis	Quantitative
44	(Tian et al., 2024)	Data from 311 Chinese manufacturers to validate SC model	Quantitative
45	(Yadav and Singh, 2024)	SC management, supplier selection, external factors	Qualitative
46	(Effah et al., 2023)	Cognitive mapping, best-worst method, AI algorithm evaluation	Quantitative
47	(Wang et al., 2023)	Supplier selection framework for upstream SC sustainability	Quantitative
48	(Ahmed et al., 2023)	Bayesian-BWM for evaluating AI-based SC imperatives	Quantitative
49	(Singh et al., 2024)	Mixed-method on AI-enabled SCs with 231 participants	Qualitative and Quantitative
50	(Lin and Lu, 2024)	Combining IDEA and ML to evaluate/predict supplier performance	Quantitative
51	(Yu et al., 2022)	Survey on SC uncertainty, IT, resilience, and sustainability (200 Chinese enterprises)	Quantitative
52	(Sharma, 2023)	The focus of the research is on developing a theoretical framework for using AI in sense-making within survival SCs during crises like pandemics.	Qualitative
53	(Ivanov, 2023)	Developing an IDT system that visualizes physical SCs in digital form, collects and processes data, mimics human decision-making, and creates new knowledge and decision-making algorithms through human-AI collaboration.	Quantitative

54	(Song et al., 2024)	The methodology of the study involves quantitative analysis. It utilizes a baseline regression model to examine the impact of AI on the vulnerability of the renewable energy SC. The study also employs trade network analysis.	Quantitative
55	(Dey et al., 2023)	Structural equation modeling on data collected from 280 Vietnamese manufacturing SMEs' operations managers.	Quantitative
56	(Byeongmok Kim and Lee, 2024)	Combination of theoretical modeling, algorithm development, and computational simulations to analyze and enhance SC resilience and viability.	Qualitative and quantitative

Abstract

The intensification and increasing intricacy of global disruptions, whether sanitary, environmental, geopolitical, or technological, underscore the imperative to reinforce the resilience and long-term viability of supply chains, particularly within critical infrastructures such as the healthcare sector. This doctoral dissertation presents a comprehensive and multi-level investigation into the potential of artificial intelligence (AI), with a focus on interpretable machine learning models, to enhance the adaptive, absorptive, and transformative capacities of supply chains operating in uncertain environments.

The first contribution is grounded in a systematic literature review structured according to the TCCM framework (Theory, Context, Characteristics, Methodology). This review delineates the range of theoretical paradigms employed, including dynamic capabilities, fuzzy set theory, and organizational information processing theory, as well as the diversity of application domains, particularly in the manufacturing, agri-food, and electronics industries. While quantitative methodologies dominate the field, the analysis identifies a critical research gap concerning the operationalization of AI for supply chain resilience, particularly in terms of model interpretability and the integration of complex, systemic risk dimensions.

The second contribution adopts an empirical orientation through an in-depth study of COVID-19 vaccine logistics in France. A predictive decision-support system based on interpretable machine learning techniques has been developed and deployed, illustrating the potential of AI tools to anticipate logistical flows, prioritize interventions, optimize resource allocation, and inform high-stakes decisions during health crises. The study highlights the crucial role of algorithmic transparency in promoting institutional trust and robust decision-making amid heightened uncertainty.

The third contribution examines the pharmaceutical supply chain serving the Andrée Rosemon Hospital Center in French Guiana during the chikungunya, Zika, and post-epidemic phases. Using hospital pharmacy consumption data, the study reconstructs clinically relevant demand shocks and evaluates their logistical effects through a discrete-event simulation model developed in AnyLogistix. The analysis assesses how epidemic-related changes in demand affect backlog accumulation, inventory position, service level, and lead time across four scenarios: the 2013 pre-epidemic baseline, the 2014–2015 chikungunya episode, the 2016 Zika episode, and the 2017 post-epidemic recovery state. The revised framework strengthens the simulation component by addressing temporal normalisation, the limits of disconnected

simulation models in comparison with Digital Supply Chain Twin approaches, and the role of network memory in recovery trajectories. The study therefore proposes a structured modelling approach for analysing pharmaceutical supply chain resilience in geographically constrained healthcare systems exposed to recurrent epidemic pressure.

Taken together, these three contributions advance the theoretical, methodological, and practical understanding of how AI—when designed for interpretability and integrated with simulation-based modeling—can serve as a strategic lever to strengthen the robustness, agility, and continuity of supply chains in the face of multidimensional crises. This work thus offers novel insights relevant to academic researchers, policymakers, and industry practitioners engaged in the governance of healthcare logistics under conditions of profound uncertainty and systemic risk.

Keywords : Artificial Intelligence (AI), Supply Chain Resilience, Interpretable Machine Learning, Healthcare Logistics, Discrete-Event Simulation, Crisis Management, Digital Twin

Résumé

L’accélération et la montée en complexité des perturbations globales , qu’elles soient sanitaires, environnementales, géopolitiques ou technologiques, soulignent la nécessité impérieuse de renforcer la résilience et la viabilité des chaînes logistiques, en particulier dans les secteurs critiques tels que celui de la santé. Cette recherche doctorale propose une analyse approfondie du rôle des technologies d’intelligence artificielle (IA), avec un accent particulier sur les systèmes d’apprentissage automatique interprétables, dans l’amélioration de la capacité des chaînes logistiques à résister, à s’adapter et à se réorganiser face aux crises.

La première contribution repose sur une revue systématique de la littérature structurée selon le cadre TCCM (Théorie, Contexte, Caractéristiques, Méthodologie). Cette analyse met en évidence la diversité des fondements théoriques mobilisés (capacités dynamiques, théorie des ensembles flous, théorie du traitement de l'information organisationnelle), la pluralité des contextes étudiés (industrie manufacturière, agroalimentaire, électronique), ainsi que la prédominance des approches quantitatives. Toutefois, elle révèle un manque de recherche spécifique sur le rôle de l’IA dans les dynamiques de résilience et de viabilité, notamment en ce qui concerne l’interprétabilité des modèles et l’intégration des risques systémiques.

La deuxième contribution adopte une approche empirique, centrée sur l’analyse de la distribution des vaccins contre la COVID-19 en France. À partir d’un scénario d’application d’un système prédictif interprétable fondé sur l’IA, cette étude met en évidence le potentiel de ces technologies pour anticiper les flux, définir les priorités, optimiser l’allocation des ressources et appuyer la prise de décision logistique en situation d’urgence sanitaire. Les résultats soulignent l’importance cruciale de la transparence algorithmique pour instaurer la confiance et garantir la robustesse des décisions dans un contexte d’incertitude.

La troisième contribution porte sur la résilience de la chaîne d’approvisionnement pharmaceutique desservant l’Andrée Rosemon Hospital Center en Guyane française durant les épisodes de chikungunya, de Zika et la période post-épidémique. À partir des consommations pharmaceutiques hospitalières, l’étude reconstruit des scénarios de demande cliniquement cohérents, puis les introduit dans un modèle de simulation à événements discrets développé sous AnyLogistix. Ce modèle permet d’évaluer la réponse logistique du système face à des chocs de demande différenciés, en analysant les niveaux de backlog, la position nette d’inventaire, les délais de livraison et le taux de service. L’apport méthodologique réside également dans la consolidation du modèle par une normalisation temporelle des résultats, une

lecture critique des trajectoires de récupération et une discussion de l'évolution possible vers un Digital Supply Chain Twin. L'étude propose ainsi un cadre structuré d'analyse de la résilience pharmaceutique pour des chaînes opérant dans des territoires isolés, contraints et exposés à des pressions épidémiques successives.

Ensemble, ces contributions enrichissent la compréhension des mécanismes par lesquels les technologies d'IA, lorsqu'elles sont conçues pour être interprétables et intégrées à des approches de simulation, peuvent renforcer la robustesse, la flexibilité et la continuité des chaînes logistiques en contexte de crise. Cette thèse apporte ainsi des contributions scientifiques, méthodologiques et opérationnelles à la gestion des risques logistiques dans des environnements incertains, au bénéfice des chercheurs, des décideurs publics et des acteurs industriels du secteur de la santé.

Mots-clés : Intelligence artificielle (IA), Résilience des chaînes logistiques, Apprentissage automatique interprétable, Logistique de santé, Simulation à événements discrets, Gestion de crise, Jumeau numérique.

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Titre : Application de l'intelligence artificielle à la résilience et à la viabilité des chaînes logistiques

Mots clés : Intelligence Artificielle, Chaînes logistiques, Management des risques, Résilience, Viabilité, Sciences des données

Résumé : L'accélération et la diversification des dynamiques perturbatrices à l'échelle mondiale, qu'elles soient sanitaires, environnementales, géopolitiques ou technologiques, soulignent la nécessité de renforcer la résilience et la viabilité des chaînes logistiques, notamment dans les secteurs critiques tels que la santé. Cette thèse propose une analyse approfondie du rôle des technologies d'intelligence artificielle (IA), dans l'amélioration de la capacité des chaînes d'approvisionnement à résister, s'adapter et se réorganiser face aux crises.
La première contribution repose sur une revue systématique de la littérature scientifique, structurée selon le cadre TCCM (Théorie, Contexte, Caractéristiques, Méthodologie). Cette analyse met en évidence la diversité des fondements théoriques mobilisés (capacités dynamiques, ensembles flous, théorie du traitement organisationnel de l'information), la variété des contextes étudiés (industries manufacturières, agroalimentaires, électroniques), et la prépondérance des approches quantitatives. Elle révèle toutefois une sous-exploration du rôle spécifique de l'IA dans les dynamiques de résilience et de viabilité logistiques, notamment en ce qui concerne l'interprétabilité des modèles et l'intégration des risques systémiques.
La deuxième contribution adopte une approche empirique fondée sur l'analyse des livraisons de vaccins contre la COVID-19 en France. À travers la conception et l'application d'un système prédictif d'apprentissage automatique interprétable, elle met en évidence la capacité de ces technologies à anticiper les flux, structurer des priorisations, optimiser l'allocation des ressources et soutenir la prise de décision logistique dans un contexte d'urgence sanitaire. L'étude souligne l'importance de la transparence algorithmique pour garantir la confiance et la robustesse des décisions en situation de forte incertitude.
La troisième contribution porte sur l'analyse de la chaîne d'approvisionnement pharmaceutique en Guyane française lors des épidémies de Zika et de Chikungunya (2015–2016). Un jumeau numérique de la chaîne a été élaboré à l'aide d'une modélisation par simulation à événements discrets via la plateforme AnyLogistix. Cette modélisation permet d'évaluer l'impact des perturbations épidémiques sur les niveaux de stock, les délais de transport et la capacité d'adaptation du système. L'étude aboutit à la proposition d'un cadre structuré de résilience pharmaceutique, applicable aux chaînes opérant en contexte isolé ou sous forte pression épidémique.
L'ensemble de ces travaux contribue à enrichir la compréhension des mécanismes par lesquels les technologies d'IA, lorsqu'elles sont conçues de manière interprétable et intégrées à des approches de simulation, peuvent renforcer la robustesse, la flexibilité et la continuité des chaînes logistiques en contexte de crise. La thèse propose ainsi une contribution scientifique, méthodologique et opérationnelle à la gestion des risques logistiques dans des environnements incertains, à destination des chercheurs, des décideurs publics et des acteurs industriels du secteur de la santé.

Title: Application of Artificial Intelligence to the Resilience and Viability of Supply Chains

Key words: Artificial Intelligence, Supply Chains, Risk Management, Resilience, Viability, Data Sciences

Abstract: The acceleration and increasing complexity of global disruptions, whether health-related, environmental, geopolitical, or technological, underscore the imperative to enhance the resilience and viability of supply chains, particularly within critical sectors such as healthcare. This doctoral research provides a comprehensive analysis of the role of artificial intelligence (AI) technologies in improving the capacity of supply chains to resist, adapt, and reorganize in response to crises.
The first contribution is founded upon a systematic literature review, structured according to the TCCM framework (Theory, Context, Characteristics, Methodology). This analysis reveals the diversity of theoretical underpinnings employed (including dynamic capabilities, fuzzy set theory, and organizational information processing theory), the breadth of contexts investigated (notably manufacturing, agri-food, and electronics industries), and the predominance of quantitative methodologies. Nonetheless, it highlights a gap concerning the specific role of AI in supply chain resilience and viability dynamics, particularly with respect to model interpretability and the integration of systemic risks.
The second contribution adopts an empirical approach centered on the analysis of COVID-19 vaccine deliveries in France. Through the development and application of an interpretable machine learning predictive system, this study evidences the potential of these technologies to forecast flows, establish prioritizations, optimize resource allocation, and support logistical decision-making in a public health emergency context. The findings emphasize the critical importance of algorithmic transparency to foster trust and ensure decision robustness amid significant uncertainty.
The third contribution focuses on the pharmaceutical supply chain in French Guiana during the Zika and Chikungunya epidemics (2015–2016). A digital twin of the supply chain was constructed utilizing discrete-event simulation modeling via the AnyLogistix platform. This model facilitates the assessment of epidemic-induced disruptions on inventory levels, transportation lead times, and system adaptability. The study culminates in the proposal of a structured pharmaceutical resilience framework applicable to supply chains operating in isolated environments or under substantial epidemic pressure.
Collectively, these contributions advance the understanding of the mechanisms through which AI technologies, when designed for interpretability and integrated with simulation-based approaches, can reinforce the robustness, flexibility, and continuity of supply chains in crisis contexts. This thesis thereby offers scientific, methodological, and operational contributions to the management of logistical risks in uncertain environments, addressing the needs of researchers, public policymakers, and industrial actors within the healthcare sector.