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Je soussigné, Ali Adeli Koudehi, déclare par la présente que le travail présenté dans ce manuscrit est mon propre travail, réalisé sous la direction scientifique de Marie-Hélène Grosbras and Stéphane Luchini, dans le respect des principes d'honnêteté, d'intégrité et de responsabilité inhérents à la mission de recherche. Les travaux de recherche et la rédaction de ce manuscrit ont été réalisés dans le respect à la fois de la charte nationale de déontologie des métiers de la recherche et de la charte d'Aix-Marseille Université relative à la lutte contre le plagiat.

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Liste de publications et/ou brevets et participation aux conférences

1) Liste des publications et/ou brevet [a] réalisées dans le cadre du projet de thèse :
    1. Adeli Koudehi, A., Aprahamian, F., Grosbras, M.-H., Luchini, S., & Teschl, M. (fourthcoming). The neuroeconomics of effort: Insights from the history of economic thought. In A. Kirman & M. Teschl (Eds.), The state of mind in economics. Cambridge University Press.
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    3. Adeli Koudehi, A., Dubarry, A-S., Teschl, M., Grosbras, M.-H., Luchini, S., (in preparation). Cognitive Effort Is Driven by Arousal, Not Valence: Experimental Evidence
    4. Adeli Koudehi, A., Dubarry, A-S., Teschl, M., Luchini, S., Grosbras, M.-H., (in preparation). In Pursuit of the Resource: How Arousal Contributes to Selective Attention?

[a] Cette liste comprend les articles publiés, les articles soumis à publication et les articles en préparation ainsi que les livres, chapitres de livre et/ou toutes formes de valorisation des résultats des travaux propres à la discipline du projet de thèse. La référence aux publications doit suivre les règles standards de bibliographie et doit être conforme à la charte des publications d'AMU.

2) Participation aux conférences[b] et écoles d'été au cours de la période de thèse :
    1. Neurodays: Neuroscience and Society, Marseille, France (Nov 2021)
    2. Cognitive Control and Performance Monitoring, Carry-le-Rouet, France (May 2022) - Poster presentation
    3. CIVIS student days: The consequences of the COVID crisis, Marseille, France (Apr 2022)
    4. Neurodays: Healthy mind in a healthy body, Marseille, France (Nov 2022) - Organizer and Poster presentation
    5. Minds at play, Marseille, France (Jan 2022)
    6. INT anniversary, Marseille, France (Sep 2022)
    7. Second international workshop on marmoset neuroscience, Marseille, France (Jul 2022)
    8. TimCog : Perspectives on temporal cognition, Marseille, France (Jun 2022)
    9. Düsseldorf Decision-Making, Online (Aug 2023)
    10. AMU-EKU bilateral symposium, Online (Feb 2023)
    11. NeuralNet GDR annual meeting, Marseille, France (Oct 2023)
    12. CuttingEEG, Lyon, France, (Oct 2023) - Poster presentation
    13. Neurodays 2023, Marseille, France, (Nov 2023) - Talk

[b] Le terme « conférence » est générique. Il désigne à la fois « conférence », « congrès », « workshop », « colloques », « rencontres nationales et/ou internationales » … etc.

Indiquer si vous avez fait une présentation orale ou sous forme de poster.

Résumé

Ces dernières années, les recherches ont enrichi notre compréhension de la prise de décision liée à l'effort cognitif, mais la notion même d'effort cognitif reste mal définie. Cette thèse vise à le caractériser et à le quantifier.

Le corps principal de la thèse comprend trois articles. Le premier résume la littérature en fonction de deux cadres conceptuels:1- la valence (coût d'opportunité du contrôle cognitif) et 2- l'éveil (intensité de l'attention sélective), liés à l'effort cognitif. Le modèle de la valence associe l'effort cognitif à une valence négative et l'évalue par sa « valeur subjective », tandis que le modèle de l'éveil l'associe à la vigilance et le mesure par des marqueurs physiologiques (taille pupillaire, variabilité cardiaque). Le modèle de la valence prédit une corrélation positive entre effort et performance, alors que le modèle de l'éveil considère cette relation comme stable.

Le deuxième article teste ces prédictions à travers une expérience originale comportant deux sessions (« N-back » et « AX-CPT ») et trois innovations : l'apprentissage de stratégies cognitives, le choix libre de l'effort, et la combinaison de mesures subjectives et physiologiques (potentiels évoqués EEG et pupillométrie). L'analyse montre que le jugement subjectif de l'effort cognitif (auto-déclaré) est corrélé à l'éveil (indexé par la dilatation pupillaire et la composante P3 des potentiels évoqués par les cibles), mais pas à la valence (indexée par la composant FRN des potentiels évoqués par le feedback). Aussi, nous avons observé que les participants continuent à fournir un effort au-delà de la durée suffisante pour terminer la tâche. De plus, à difficulté égale, l'effort auto-déclaré ne prédit pas la performance. Une stratégie particulière dans la tâche N-back réduit l'effort perçu tout en améliorant la performance, remettant en cause l'idée qu'un effort accru améliore systématiquement la performance. Enfin, une corrélation

négative entre le taux de microsaccades et l'effort auto-déclaré suggère que ce marqueur pourrait complémenter la pupillométrie.

Le troisième article examine de plus près l'approche de l'effort cognitif fondée sur l'éveil. Il examine pourquoi l'effort est étroitement associé à l'éveil et explore le concept de « mobilisation des ressources » du point de vue du traitement des signaux. Il émet l'hypothèse que l'excitation renforce l'intensité de l'attention sélective en accélérant la synchronisation neuronale, augmentant ainsi le débit d'information. S'appuyant sur l'hypothèse du « binding-by-synchrony », l'article développe et teste un modèle formel à l'aide de données empiriques. Les résultats révèlent que l'éveil, indexé par la dilatation de la pupille, interagit positivement avec le couplage entre la phase de basse fréquence et l'amplitude de haute fréquence, mesuré par l'indice de modulation, pour prédire la performance de la tâche (succès ou échecs). Ces résultats suggèrent que l'excitation facilite la liaison rapide des caractéristiques pertinentes pour la tâche par le biais d'une synchronisation neuronale plus rapide, ce qui offre de nouvelles perspectives sur les mécanismes computational qui sous-tendent l'effort cognitif et la mobilisation des ressources.

Enfin, la discussion générale reprend les deux cadres conceptuels identifiés et explore l'origine de l'aversion à certaines tâches exigeantes. Elle propose une définition descriptive de l'effort cognitif et souligne les limites et les perspectives futures.

Mots clés : Effort cognitif, Neuroéconomique, Contrôle cognitif, Éveil, Valence

Abstract

Much research especially in recent years has greatly advanced our knowledge about how we make a decision about cognitive effort; yet the knowledge about cognitive effort itself has lacked behind. That is why this thesis is set out to define and quantify cognitive effort.

The main thesis body comprises three articles. In the first article, we summarize the literature on cognitive effort into two approaches: valence (opportunity cost of cognitive control) and arousal (intensity of selective attention). The two approaches have distinct (but not mutually exclusive) predictions about phenomenology, measurement of cognitive effort and its relationship with performance. As the name of the two approaches indicates, the valence approach puts greater emphasize on the association of cognitive effort with negative valence and aversiveness, while the arousal approach emphasizes more on the association of cognitive effort with arousal and alertness. The valence approach measures cognitive effort by its price (i.e. "subjective value") and the arousal approach measures cognitive effort by physiological markers of arousal (e.g. pupil size, heart rate variability). Last, the valence approach envisions a positive relation between cognitive effort and performance, (more effort leading to better performance), whereas the arousal approach holds a null relation view between effort and performance within a difficulty level and at a given pace.

To test the predictions of the two approaches, the second article presents a novel experiment consisting of two separate sessions: one with N-back and the other with AX-CPT tasks. The experiment has three distinctive features. First, we train participants with different "cognitive strategies". Second, it introduces a new behavioural measure, "free choice of effort". Third, it combines self-reports of cognitive effort, valence, and arousal with common physiological measures, including

pupillometry event-related potential of EEG: “feedback-related negativity” for the valence approach and the “P3” and pupil dilation for the arousal approach.

The results favoured the arousal approach: reported cognitive effort correlated positively with self-reported arousal, P3 amplitude, and pupil size. However, it did not correlate with reported valence or the feedback-related negativity (FRN). This was further confirmed by the participants' free choice of effort; they exerted more cognitive effort than was necessary to collect required number of points to pass the experiment. Additionally, performance at the same level of difficulty showed no correlation with reported effort. Cognitive strategies played a significant role. Specifically, in the N-back task, one strategy led to reported effort while delivering a higher level of performance. This casts doubt on the general assumption that more effort leads to higher performance.

The third article takes a closer look at the arousal approach to cognitive effort. It examines why effort is closely associated with arousal and explores the concept of “resource mobilisation” from a signal processing perspective. It hypothesises that arousal enhances the intensity of selective attention by accelerating neural synchronisation, thereby increasing information throughput. Building on the “binding-by-synchrony” hypothesis, the article develops and tests a formal model using empirical data. The findings reveal that arousal, indexed by pupil dilation, positively interacts with the coupling between low frequency phase and high frequency amplitude of frontal electrods, measured by the Modulation Index, to predict task performance (hits versus misses). These results suggest that arousal facilitates the rapid binding of task-relevant features via faster neural synchronisation, offering new insights into the computational mechanisms underlying cognitive effort and resource mobilisation.

The general discussion explores possible sources of the aversiveness of certain effortful tasks. A descriptive definition of cognitive effort is proposed, and limitations and future research directions are highlighted.

Keywords: Cognitive effort, Neuroeconomics, Cognitive control, Arousal, Valence

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First and foremost, I want to express my deep appreciation to the members of the jury who accepted to take part in this thesis defence. Their research has greatly shaped my thinking; some of which is reflected in this thesis, while some is not. I feel fortunate to have your attention and to be able to present my work before such an interdisciplinary jury.

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Preface

This thesis focuses on the neuroeconomics of cognitive effort. Here, we provide an overview of the integration of economics and neuroscience into the field of neuroeconomics and its methodological considerations, with a focus on the study of effort. We argue that, despite being part of the field since its inception, effort has largely been overlooked. Even though there has been great amount of research on the decision about effort yet research on effort itself has been scarce. The aim of this thesis is to address this oversight by demonstrating that effort merits the same level of recognition as other key topics in neuroeconomics, such as risk, time and altruism (Camerer et al., 2005).

The first chapter of the book Neuroeconomics (Glimcher et al., 2014) provides a brief history of the field. The authors identify the first neuroeconomic study as 'On the Neural Computation of Utility' by Peter Shizgal and Kent Conover (1996). This article aimed to locate the economic concept of “utility” in the brain — utility being a common currency for evaluating choices. The article also sought to establish a general normative theory of higher cognitive functions — a project that continues in studies on risk, time and altruism. To this end, the authors designed an experiment in which an animal could press a lever to trigger electrical stimulation of the medial forebrain bundle (“reward” processing area of the brain). The researchers demonstrated that the animal's decision to exert effort reflected its attempt to maximise its reward or utility.

“We assume our rats to be rational consumers insofar as they will prefer, under non-satiating conditions, an alternative that provides more of a given appetitive goal object (e.g. food) over an alternative that provides less. The relative utility of two different goal objects will depend not only on their abundance but also on the physiological state of the consumer and the ecological context in which the goal objects are embedded. In

effect, we treat utility as a subjective estimate of the potential contribution of a goal object to fitness. The more accurate the estimate, the more adaptive are the choices that take the utility value into account."

It is interesting that they consider their rats as commodity consumers. One can also consider them as labourers. After all, they were exerting effort. The activity in question leads to different outcomes (e.g. food consumption or brain stimulation) and also seems to involve effort. Perhaps a better understanding of utility could explain why the rat subjects were considered utility consumers rather than labourers who exerted effort.

An interesting discussion of utility can be found in the third chapter of The Theory of Political Economy (1871) by William Stanley Jevons, who is widely regarded as one of the founding figures of marginalist thinking in economics. The chapter starts with the following passage: "Pleasure and pain are undoubtedly the ultimate objects of the Calculus of Economics. To satisfy our wants to the utmost with the least effort".

In this chapter, the commodity is pleasure (that we approach) or pain (that we avoid). Jevons used the term "utility" to justify the "pain" or effort involved in acquiring a commodity: "the term utility denotes the abstract quality whereby an object serves our purposes and becomes entitled to rank as a commodity", and "anything which an individual desires and labours for must possess utility for him'. A commodity (e.g. food or electrical stimulation) is a reward after pain or something that is worth the pain. The pain we pay for is the effort that is assumed to be painful. In this formulation, labourers and consumers are one and the same, and Shizgal and Conover were spot on. Consumers pay for the commodity through the pain of losing money and labourers pay for it through the pain of their effort. This definition of a commodity assumes a quid pro quo trade: the pain experienced before receiving the commodity must be equal to the pleasure experienced after receiving it, in the eyes of a rational mind. But how did Jevons defend his assumption that the effort of labour equates to pain?

In the fifth chapter of the book, Jevons's famous "labour supply theory" (LST) resides. In the first instance, Jevons defines labour as *"all exertion of body or mind"* but immediately after he explicitly excludes the pleasurable exertion of body or mind like a game of cricket as irrelevant to his theory of economics. Thus, his definition of labour restricts to: *"any painful exertion of mind or body undergone partly or wholly with a view of future good"*, the good, or the commodity that was defined before as having utility to worth the pain of its production. This leads to a logical circularity often found in marginalist arguments: a commodity is necessarily pleasurable because it follows the painful effort, and effort is necessarily painful because it precedes the pleasure of the commodity.

However, Jevons himself was aware of the problem of considering labour as only painful, as he clearly states in a footnote to his definition of labour in the second edition of the book. He writes: "The subject presents itself to me as one of great difficulty, and it is possible that the true solution will consist in treating labour as a case of negative utility, or negative mingled with positive utility … every act, whether of production or of consumption, may be regarded as producing what Bentham calls a lot, both of pleasures and pains…".

Jevons himself readily acknowledges the problem with this definition of labour, which is clearly illustrated by this example: if one enjoys one's job, then it's no longer labour. Does that mean that the labour does not need to be compensated? Does changing the way one does their job in such a way that it becomes more pleasant mean that it is no longer labour? (See chapter 2)

While it may be intuitive to revisit economic assumptions developed before the human brain could be studied using modern methods, some neuroeconomic approaches, particularly those related to cognitive effort, still appear to rely on such foundations (as discussed further in Chapter 2). Notably, the application of LST to explore higher-level cognitive functions such as cognitive control is especially noteworthy, given that

the economic study of effort has evolved significantly beyond traditional textbook models over the past two decades.

The trouble with the LST is that it contradicts the empirical observation that higher wages lead to greater effort (Akerlof, 1982, p. 364). This was first seen in the “stated effort” experiments, in which participants only had to state their level of effort given the proposed wage. In the “real effort” experiments, which came later, the participants not only stated their level of effort, but also had to put this into practice (for a review, see Charness et al., 2018; Fehr et al., 2007). The results of these experiment have consistently been that employees pay labour (hourly work) above “market clearance” wage (reward) and the employers who could have exerted effort at the minimum level, they decide to exert above the minimum point.

These findings contradict the LST because it predicts that the intensity of labour (effort) depends on the wage (reward). As wages (the reward) are fixed and independent of effort, the LST predicts that effort should not change with higher wages. The explanation given for these findings, known as “gift exchange theory”, is that the employee and employer are engaged in a social game: the employer “gifts” the employee with a higher wage, and the employee reciprocates with increased effort. However, this theory also has a problem regarding effort: what does "real effort" mean, and how is it really measured?

An alternative perspective on neuroeconomics can be traced back to earlier theoretical models. Perhaps the seminal work about motivation and performance is Donald Hebb's 1955 paper, “Drives and the Conceptual Nervous System”. This work provided the theoretical basis for the Yerkes–Dodson law, which describes the inverse U-shaped relationship between autonomic arousal and performance. In response to the notion that reward serves as a motivating force, Hebb argues that rather than merely being pulled by reward, a general drive exists that pushes us, as indicated by the level of arousal. This drive continuously seeks avenues for discharge, in order to find peace and

relieve pressure. This applies not only to basic needs such as hunger and sex, but also to more intense activities such as exploration and even “problem-seeking behaviour”.

Beyond its scientific content, the methodological argumentation in Hebb's paper provides invaluable insights for contemporary neuroeconomics. The paper addresses the central problem of the role of the nervous system in giving rise to motivation and drive. As Hebb articulates: “The problem of motivation of course lies close to the heart of the general problem of understanding behavior. In great part, the difficulty concerns that c.n.s., or conceptual nervous system… But the conceptual nervous system of 1930 was evidently like the gin that was being drunk about the same time; it was homemade and none too good … If we must drink, we can now get better liquor; likewise, the conceptual nervous system of 1930 is out of date and - if we must neurologize - let us use the best brand of neurology we can find.”

This critique closely aligns with the concerns raised in economic neuroscience, where a key principle is that any attempt to integrate economics into neuroscience must be based on the most rigorous and latest economic theories. However, what is perhaps even more valuable about Hebb’s work is not just his conclusions, but also the thoughtful approach he takes to reach them. What distinguishes his 1955 paper is its integrative spirit. Rather than focusing on mapping economic concepts onto brain function and building normative models of brain behaviour, Hebb pursued a broader synthesis. His approach sought coherence among neurophysiology, psychology and economics. Starting from what was then known about neuroscience, he proposed that the nervous system is intrinsically self-motivated and that, if it fails to activate and engage itself, it experiences more fundamental problem: “The human brain is built to be active, and that as long as it is supplied with adequate nutrition it will continue to be active. Brain activity is what determines behavior, and so the only behavioral problem becomes that of accounting for inactivity.”

This argument becomes particularly compelling when we consider instances when our fatigued bodies yearn for rest at night, but our restless minds refuse to let us sleep.

Hebb references the “sensory deprivation” experiment of Bexton and Scott (1954) which it can be well understood as a neuroeconomic study. In this experiment participants were offered $20 per hour — equivalent to six days' minimum wage at the time — to spend the day doing nothing. Contrary to the predictions of LST and Gift Exchange, within just a few hours all the participants were asking for something to do (e.g. teaching children about the dangers of alcohol). This experiment provided empirical evidence for the “self-motivating drive” that Hebb describes : individuals are driven to seek effortful activity, despite the allure of the effortless reward.

This neuroeconomic perspective, which seeks to create harmony between fields rather than transfer theory from one field to another, can also be found in Robert Shiller’s talk at the 2011 Society for Neuroscience meeting. Shiller rejected the standard rationality assumption of economists by using the term “animal spirits”, borrowed from Keynes (1936), to describe the financial crisis of 1929: “Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than on a mathematical expectation, whether moral or hedonistic or economic. Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as a result of animal spirits - of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities”.

What does the term 'animal spirit' mean? The term “spiritus animalis” was coined by Claudius Galenus in 150 AD while studying the human nervous system. He believed that these nerves somehow give rise to the characteristics of the human psyche and behaviour. In other words, it refers to anything that originates in the nervous system. In his talk to neuroscientists, Shiller suggested that the neuroeconomics emerging after the 2007 financial crisis could play a role similar to that of Keynesian economics in the wake of the 1929 Great Depression. Rather than a reinforcement of the existing assumptions, neuroeconomics has the capacity to help reorient economic thinking by

listening closely to what neural activity might reveal. In this view, neuroeconomics offers not just a new set of tools, but also a chance to develop new hypotheses and economic theories.

This project began with the observation that, although effort is a pervasive concept in economics and cognitive neuroscience, it is rarely defined explicitly. This point is elaborated in the general introduction. Our aim was therefore to conduct a thorough review of the different perspectives on effort in both disciplines to determine whether it would be possible to develop a useful and practical definition of effort. In doing so, we identified an older body of literature on cognitive effort, summarised as the "arousal approach", which shares some commonalities with, but also presents important difference to, the more recent "valence approach" of cognitive effort, as discussed in Chapter 1. Recognising the necessity of comparing these two models to fill the existing literature gap, we designed an experiment to reconcile them in Chapter 2. This sets the stage for a more profound delve into the arousal approach and more specific measurement of cognitive effort in Chapter 3 and contributes to the various issues in which cognitive effort plays a role, as discussed in the general discussion at the end.

General Introduction

The general introduction of this thesis aims to provide a historical overview of key economic concepts that underpin contemporary neuroeconomic approaches to the study of cognitive effort. By tracing the intellectual lineage of notions such as labour, cost, and incentives, we highlight how these foundational ideas have evolved and become integrated into interdisciplinary frameworks that combine economics and cognitive neuroscience. This retrospective not only contextualizes the emergence of neuroeconomics as a field but also clarifies the conceptual tools it inherits from classical and behavioral economics.

Moreover, the introduction argues for the necessity of a neuroeconomic approach to cognitive effort—one that requires economists to engage directly with cognitive neuroscience in order to rigorously examine the cognitive processes underlying making effort. This rationale provides the conceptual and methodological groundwork for the first chapter, which presents a detailed review of the cognitive neuroscience literature on cognitive effort, setting the stage for a cross-disciplinary synthesis.

The Neuroeconomics of Effort: Insights from the History of Economic Thought[c]

1 Introduction

When we stumbled over the article by Gailliot et al. (2007), we were immediately captured by the story it told: when individuals engaged in an effortful self-control task, their performance dropped in a subsequent cognitively demanding task, in comparison to those who did not do an effortful task first. While this observation per se does not look so surprising – after all, do we not all have the experience of exhaustion after engaging in some cognitive effortful tasks? – it is the reason – and the solution – they advance why this is so: when we do some effortful tasks, we "deplete" some limited energy resource. And this resource is glucose. Drinking a sugar lemonade is restoring this energy resource and the performance drop will be offset. It's the lemonade, stupid!

Contemporary economists generally assume that monetary incentives have an impact on performance via an increase in effort. Labour market models assume that labour supply increases positively with wages. As wages go up, opportunity cost for leisure increases and people will work more. However, with the concept of "efficiency wages" as it was developed in the late 70s and 80s, the notion of "effort" emerged as an independent concept in addition to "labour". While "labour" corresponds to some baseline effort that workers are willing to exchange for hourly market equilibrium

[c] This section was originally prepared for inclusion in a forthcoming book chapter.

wages, “efficiency wages” paid more than those wages and thus incited workers to “upgrade”, as it were, their effort per hour.

Clearly, if it’s not money, but sugar that makes the difference for sustained effort, this would be a completely different story. For example, if individuals increase their effort in response to incentives, this can deplete their energy resources and ultimately lead to a drop in performance at some stage. And even if people stay focussed throughout their working hours and performance does not drop, maybe it does so after they leave for home. One of Gailliot et al.’s (2007) experiments show that an effortful self-control task is followed by a reduction in helping or pro-social behaviour. Hence it may well be that the economists’ concern for higher performance, and thus greater effort, is negatively impacting marital, family or other aspects of people’s social life. This is not (yet) a big topic for economists, but there are some studies on (negative) spillovers of “high-performance management” on people’s work-life balance for example in other fields of the social sciences (see e.g. White et al. 2003). Given economists’ concern about individual and social welfare, any externalities of such “effort enhancement strategies” on people’s life should clearly be analysed in more detail, because they may feedback, eventually, in reduced performance or productivity.

We were thus hooked to the question of effort. We figured out that it is such a crucial variable in many mainstream economic models, but actually, we do not quite know what it is and does and how it functions.

Contemporary economists are actually aware of this. They readily admit that effort is usually not observable, nor verifiable, only outcome may be (see e.g. Cahuc, Carcillo and Zylberberg, Chapter 6, p.214). In a world of division of labour, where “principals” hire “agents” in order to make the latter do certain jobs for the former, there is a lot of imperfect information about the provided effort. Economists are thus investigating which contracts offer the right incentive and payment structure so that it is in the interest of the “agent’” to invest the greatest possible effort, which is assumed to be costly to them, but beneficial for the principal (see e.g. Laffont and Martimort 2002).

But what if economists knew more about what effort is and does? Illuminating the black box of effort may be helpful to better understand the effect of what effort does to people, how incentive impact effort and how effort translates into performance, and whether there are other dimensions, such as bodily energy resources for example that need to be taken into account for effort "production". After all, economists' concern is about "embodied effort", that is effort done by people, with a brain and a body. It is clear that doing more or less effort has an impact on our brain and body, whether it is physical or cognitive effort. This information can therefore be important for economists to know and can consequently impact how we think about labour contracts.

So, we went to see our colleagues from the cognitive and neuroscience department. We discovered that they face similar incomplete information problems: there are a number of neuropsychological tests following brain injuries or other cognitive problems whose outcome is dependent on the effort patients are employing in answering them (e.g. Green 2006). Clinical neuroscientists are thus interested in knowing how to detect "neuropsychological malingering" to differentiate between those who do effort from those who do not, to give the correct diagnosis (e.g. Dunn et al. 2001). Moreover, poor mental or cognitive effort is considered to be a symptom for neurological conditions such as schizophrenia, depression, and other disorders (e.g. Gorissen et al 2005, Westbrook and Braver 2015). The unwillingness to overcome effort to achieve certain goals or rewards is a common feature of many neuropsychiatric and neurological disorders (Walton and Bouret 2019). On the "positive" side, the cognitive process of learning will also be influenced by effort and cognitive scientists' study under which conditions effort can be increased for better learning results (e.g. Jarvis et al. 2022). Hence the question there as well is: what actually is and does effort?

Together, we thus set out to explore the question of effort. We soon figured out that there was a burgeoning neuro-economic literature on effort, quite critical of the resource account. For example, it has been criticised that the theory was verified in the special case when subjects fasted before drinking a sweet lemonade, but not for those

who did not (Kurzban 2010, p. 251). However, it was not so much the behavioural observations such as a drop in performance over a series of cognitive effortful tasks that they put in question, but its explanation. The idea of a limited resource was said to be a "frankly unnecessary" assumption (Botvinick and Braver 2015, p. 93) to explain the dynamics of cognitive control. Instead, "[…] glucose is a *signal* rather than a *resource*" (Kurzban et al. 2013, p. 674) and acted as a reward. In fact, it has been observed that the depletion effect could be prevented by offering performance incentives (Muraven and Slessareva 2003). Depletion thus is a motivational phenomenon, rather than a constraint, critics argued. This neuro-economic literature developed for example the idea of labour/leisure trade-offs in cognitive control (Kool and Botvinick 2014) or opportunity cost models of subjective effort (Kurzban et al. 2013) with the idea that it is not that people *cannot* engage in sustained cognitive effort, it is that they *do not want to* when they are not motivated to do so.

But hold on – is this not what economists said all along? Is the neuroeconomics of effort mainly using economic models of decision making and adapting them to the brain? Is the brain making decisions such as economists say that people do? What is so surprising about that, one may ask, given that those brains are people's brains. The point is that it is an *assumption*, as much as the criticised assumption of depletable resources. It is a story those researchers tell to interpret their observations. Moreover, in economic models, effort is a black box! That's why we set out to look into the cognitive neuroscience literature to know more about effort in the first place, only to find ourselves where we started! Moreover, a little bit of history of economic thought (which may not be known by neuro-economic neuroscientists) tells us that "opportunity costs" is a concept that has been introduced to replace the concept of "disutility" or the subjective experience of labour – considered to be unmeasurable – with a measurable quantity, namely forgone wage-earnings. This was an important step towards the development of the now mainstream contemporary leisure-income/consumption model as the basis for labour supply decisions. But this step has been criticised as an "epistemological paradox": "The epistemological paradox lies in

the omission of labour in the standard modelling of its supply. Labor, both the word and the concept, vanishes in the leisure-income analysis shaping a paradoxical labour-less labour supply model" (Derobert 2001, p. 198; see also Spencer 2009). Are we now dealing with an effort-less neuroeconomic approach to effort, where effort vanishes at the expense of some cost-benefit computations?

We will show in the next section that it is not quite as bad. The cognitive and neuroscientific literature on effort and its ramification into brain injuries, cognitive disorders or other domains such as learning is huge. Here we will concentrate on a selection of highly prominent (neuro-economic) papers currently discussed in the literature, in order to give a rapid (and necessarily sketchy) perspective on what happens when we engage with effortful cognitive tasks.[d] The third section will reconsider the question of effort in contemporary economics and engage with some of the neuroeconomic concepts we discussed in section two from an economic/history of ideas point of view. Section four will summarise our discussion and highlight some possible routes of common research for cognitive and neuroscientists together with economists.

[d] There is no objectivity in our selection of papers other than to say that these papers come up very prominently in searching machines and are greatly cited, including among themselves. Their authors are mainly male US-American or US-based authors. Obviously, there are other important researchers elsewhere too, notably also in France such as neuroscientists Sébastien Bouret, Mathias Pessiglione and their colleagues (e.g. Bénon et al. 2024). For an interesting discussion about the different neuroscientific and cognitive definitions of effort see also Massin (2017) and Bermúdez and Massin (2023).

2 Cognitive psychology and neuroeconomic studies of effort

There is a flourishing neuroeconomic literature on cognitive effort, and most of them have one thing in common: effort is considered to have "negative utility" and to be "costly" (Kool and Botvinick 2018, p. 899). The subjective experience of effort is said to be "aversive" (Kurzban, Duckworth, Kable and Myers 2013, p. 662, Kool and Botvinick 2014, p. 131), which people "seek to avoid" (Kurzban et al. 2013, p. 672). "There is a long tradition within psychology of characterizing humans as "cognitive misers" who conserve effort, all else being equal" write Westbrook, Kester and Braver (2013, p.1). Inzlicht, Schmeichel and Macrae (2014) argue that "[…] people generally avoid hard work […]" (p. 129). Shenhav, Musslick, Lieder et al. (2017) ask why people do not always perform at the highest level of which they are capable and give an intuitive answer by introspection: "[…] we are constitutively reluctant to mobilize all available cognitive resources." (p. 102).

To justify this view apart from introspection, many refer to Clark L. Hull's "Principles of Behavior" (1943) in which he develops the "Law of least work", which these authors seem to take to the letter. Recently though, the notion of an "effort paradox" has been introduced (Inzlicht, Shenhav and Olivola 2018) by which is meant that people can experience effort as valuable in certain cases. The literature of "learned industriousness" is cited in that respect (Eisenberger, 1992) which means that if effort is consistently rewarded, people become more willing to exert it.

But what is this effort or what is it that is so effortful when we engage in some cognitive tasks? Reading across the literature, there is one notion that consistently comes up, and this is "control": self-control and cognitive control that is needed to achieve our goals.

There is an equally large and thriving literature well beyond neuroeconomics of effort on cognitive control or cognitive control-strategies in psychology and the neurosciences since at least the 1960s. The book on "Plans and the Structure of Behavior" by Miller, Galanter and Pribam (1960) is cited by several authors as being among the first ones to study necessary cognitive mechanisms in the process of achieving one's goals (e.g. Botvinick and Braver 2015; Pressley and Harris 2008/2009)

"Cognitive control refers to the processes or mechanisms invoked in generating or regulating behavior when that behavior goes beyond the application of learned stimulus-response associations" defines for example Cooper (2010, p. 598)[e]. In other words, cognitive control is activated when habitual responses are not sufficient to achieve a particular goal. Similarly, Inzlicht, Shenhav and Olivola (2018) write that "Effort is a volitional, intentional process, something that organisms apply, and as such, it corresponds to what organisms are actively doing and not to what is passively happening to them." (p. 338) Hence effort and cognitive control are strictly linked, increased cognitive control is effortful notably in comparison to habitual and automatic processes which are effortless (see also Kahneman 2011). "[C]ognitive control may be viewed as the force through which cognitive effort is exerted" write Shenhav et al. (2017, p. 101).

Examples of cognitive control are "response inhibition", that is actively inhibiting a prepotent or dominant response that may not be the correct one; "task shifting", that is changing between different task related stimulus-response associations; and

[e] Richard P. Cooper is a British-based cognitive scientist who has edited two interesting special issues in *Topics in Cognitive Sciences* which explore the question of whether cognitive control is "componential", i.e. an interaction of different control mechanism with particular purposes, or "emergent", that is, a construct that has no causal or explanatory utility (Cooper 2010, 2011).

"memory monitoring/updating", which requires monitoring of new information for appropriate revisions of elements that are held in the working memory (Miyake et al. 2000). Others suggest that there may be a whole "menagerie" of putative control mechanisms in addition to the three mentioned above, such as performance monitoring, conflict monitoring, and task setting, to name a few (Cooper 2010, p. 607). These control mechanisms are what the "mind" does when an individual solves a task, but individuals can also consciously employ cognitive "strategies" to solve a task or to achieve a goal. Pressley et al (1985) for example say "A strategy is composed of cognitive operations over and above the processes that are natural consequences of carrying out the task, ranging from one such operation to a sequence of interdependent operations. Strategies achieve cognitive purposes (e.g., comprehending, memorizing) and are potentially conscious and controllable activities." (p. 4). Control strategies are thus knowledge about procedures of how to get things done. "Metacognition" is the term used to indicate that an individual may have knowledge about the utility or value of certain strategies in solving particular tasks (Pressley and Harris 2006, p. 78). Strategies are divided into three broad categories: goal-specific strategies (e.g. a rehearsal strategy to memorise words), monitoring strategies (e.g. checking whether the used strategy is effective), and higher order strategies (planful sequencing of different strategies, e.g. of goal-specific and monitoring strategies) (Pressley et al. 1987).

Cognitive control mechanisms in the brain and conscious strategy selection may thus overlap and reinforce each other. Strategies can be part of a "proactive control mode" of the brain. That is, there are "early selection" strategies, enacted prior to the cognitively demanding task "[…] in order to optimally bias attention, perception and action systems in a goal-driven manner." (Braver 2012, p. 106). This contrasts with a second control "mode", called reactive control, which acts as a "late correction" mechanism and will be engaged only when needed after an interference or incongruence has been detected. "Thus, proactive control relies upon the anticipation

and prevention of interference before it occurs, whereas reactive control relies upon the detection and resolution of interference after its onset." (Braver 2012, p. 106).

The proactive control mode is said to be "top-down" because the (voluntarily chosen) goal is being maintained throughout the task and facilitates the processing of upcoming but expected events. The reactive control mode is "bottom-up" reactions to goal-maintenance and is transient, responding only when an interference or conflict has been detected. The literature refers to these two modes as the "dual mechanisms of cognitive control", first presented in Braver, Gray and Burgess (2007). This view integrates into a larger field of research on dual-process theories, which distinguishes between some more habitual, automatic and "effortless" cognitive processes and those that are more controlled and "effortful" (e.g. Chaiken and Trope 1999, Kahneman 2011). Although less parsimonious than a single process of cognitive control, a dual process theory has certain explicative advantages for cognitive functioning. For example, the reactive mode is less "resource consuming" (Braver 2012, p. 108, Box 1) as it is activated only when needed. This also means that other goals can be carried out until this reactive control is triggered by some interference. The advantage of proactive control is the continuous adaptation to facilitate goal achievement. The disadvantage may be "proactive interference", which refers to the distraction by previously relevant material when it continues to intervene while solving a new or modified task (Jonides and Nee 2006). Overall, however, as Daniel Kahneman already said with respect to his theory about our mental life as being composed of an (automatic and fast) system 1 and an (effortful and slow) system 2: "The division of labour between System 1 and System 2 is highly efficient: it minimizes effort and optimizes performance." (Kahneman 2011, chapter 1).

To learn and assess such cognitive control functions, experimental setups with particular cognitive tasks have been developed that focus on one or the other of such cognitive control functions. The Stroop task for example is widely used and tests response inhibition in particular (Stroop 1935). Subjects are presented with words

printed in different colours and the subject is asked to state the colour in which the word is written. Congruent words are those words where the meaning of the word, for example "red" corresponds to the colour in which it is written (the ink colour red), incongruent words are those whose meaning ("red") do not correspond to the ink colour (e.g. blue). In the latter case, the subject thus has to inhibit from saying "red" despite reading the word, which is the dominant response, and should correctly name the ink colour "blue". A proactive control in this kind of task would be to keep in mind, from the beginning onwards, the goal of the task ("I need to respond to ink colour, not read words") and thus be "prepared" for expected incongruency. With reactive control, it is at the moment of noticing the incongruence between the meaning of the word and the colour in which it is written that the goal of the task is reactivated (see Figure 1 in Braver 2012, p. 107). This also shows that the control mode (proactive or reactive) can become a particular strategy when subjects are instructed to solve a particular task with either of those strategies in mind.[f]

This raises the question of whether cognitive control is a "capacity" that can be modulated or improved through training. Research shows that there clearly is a developmental perspective to cognitive control. As children grow older, they increasingly learn to engage in cognitive control and to respond less to habitual behaviour (Munakata, Snyder and Chatham, 2012). Over the years, adults can show age-related impairments of cognitive functions (e.g. Paxton et al., 2006). Training for particular tasks, such as for example response inhibition, cognitive flexibility or working memory, has some effect on improved control processes and performance for particular tasks. This is referred to as "near transfer". For example, older subjects can, with specific training, achieve similar results as younger adults on some particular

[f] Strictly speaking, this implies that the reactive control mode becomes a proactive strategy.

cognitive tasks (e.g. Paxton et al., 2006). However, there are mitigated results related to the impact of training on other domains of decision making, or on other brain functions, which is named "far transfer" (e.g. Ganesan et al., 2024, Niebaum and Munakata, 2023).

Another important aspect of cognitive control is motivation. Motivation can be "manipulated" by using monetary incentives or other payments.[g] How, if ever, do incentives or rewards enhance cognitive effort: is it in terms of an "energising" function that increases response time for example, or is it in terms of the enhancement of some particular cognitive control or executive functions? Bonner and Sprinkle (2002, p. 304) suggest two aspects of effort. One is to look into how incentives or payments impact effort (or cognitive control), and the second is how effort impacts performance. Botvinick and Braver (2015, p. 87) add as a third aspect the question of how motivation impacts the temporal dynamics of cognitive control, that is, effort over time or multiple, consecutive tasks: do incentives extend effort over time and if yes, in what way? They also point out that studying these different aspects is important to disentangle an otherwise circular aspect of effort: effort is said "[…] to explain the relationship between incentives and performance, but it is also measured or inferred from the observed relationship between the two." (Botvinick and Braver 2015, p. 94). In that sense, effort often acts at the same time as the explanans even though it also is the explanandum.

To give an example, Krebs, Boehler and Woldorff (2010) present the result of a Stroop task in which subjects could earn some small monetary reward with respect to two out

[g] However, some psychological literature differentiates between "extrinsic" motivation (being motivated by something extrinsic to the task, such as money), and "intrinsic" motivation (being motivated by the task itself, or some other goal "within" the person) (e.g. Ryan and Deci 2000).

of four ink colours when they reacted fast and correctly to the task relevant aspect "ink colour" instead of the "task irrelevant" written colour word. Krebs et al (2010) find that subjects responded faster in potential-reward trials as compared to no-reward trials, and performance increased as error rates went down significantly. This suggests that the reward reduces the interference of irrelevant stimuli (the meaning of the written word) and helps subjects to focus on the task relevant aspect (the ink colour). However, they also observed that when words meant the reward-related colour but were written in the non-reward related ink colour, responses became slower, and performance decreased. Hence the reward related association with a particular colour caused greater interference in some of the incongruent trials in comparison to the situation with no payments. Said differently, while the reward helps to focus on the task relevant aspect, which is the rewarding ink colour, it also seems to cause an interference which the Stroop task is exactly meant to suppress, namely, not to pay attention to the meaning of the word. In that case, the reward causes a cognitive "bias" because the salience of the rewarding colour spreads over to task irrelevant aspects and thus decreases performance.

In an experiment with a modified and incentivised Stroop task using images of houses or buildings (instead of colours) and words, Padmala and Pessoa (2011) also show that performance was improved with respect to the non-reward condition, measured in terms of a reduction in response time. In that experiment, a "cue" of either "$20" or "$00" was shown on the screen before each trial to indicate the "motivational context" of reward or no-reward. They also used brain imaging during those tasks to see how network interactions support the impact of reward on cognitive control, thus looking specifically how the cue-related responses (the reward or motivational context) influenced the target-related responses (responding to images but not to words). They found an inverse linear relationship between cue and target responses. That is, as cue-related responses increased notably in fronto-parietal cortical regions which are associated with attentional control, target related responses decreased in the medial prefrontal cortex (MPFC), which is implicated in conflict processing. They thus

interpret these findings as suggesting "[…] that motivationally salient cues enhanced top-down control, thereby reducing conflict-related responses (as well as reducing behavioral conflict) – and thus increasing the likelihood of reward." (p. 3429). In particular, they argue that enhanced attentional control reduces the impact of word stimuli, that is of non-target information. The reduced impact of word stimuli, or the "filtering" of task-irrelevant stimuli, it is argued, is then reducing the amount of conflict in the MPFC. Said differently, "[…], participants are able to employ motivationally salient cues to upregulate top-down control processes that bias the selection of visual information in a way the reduces both behavioral conflict and conflict-related brain responses." (p. 3430) Interestingly however, they notice that this filtering of word stimuli meant that in congruent trials, performance was actually reduced in the reward condition. Congruent trials are typically said to be easier than incongruent trials because of the correspondence of the image with the word but given that less attention is paid to the word with incentives, the advantage of "seeing the congruence" may have been diminished because of the rewards-caused saliency.

Given these examples, it looks as if motivation does not "energise" effort in some unspecified way but rather influences particular cognitive control functions or mechanisms. However, this does not mean that performance will improve in all respects. While the "sharpening" of some control functions, such as the filtering of task-irrelevant stimuli or emphasising of task-relevant aspects, improves performance, it is precisely these features which reduce performance relative to other features of the task, and in particular those that are not rewarded. Hence if reward is used as an indiscriminate carrot with the idea to improve performance overall, this may not work, much in the "freakonomic" sense that there are "hidden sides of everything" which may distort outcome in unexpected ways (Levitt and Dubner 2005).

If motivation, stimulated by rewards, do shape and influence particular aspects of effortful cognitive control, this seems to suggest that effort is not some unspecific increase in energy. There is an old debate on the "energy costs of mental effort"

(Sourkes 2006) in the history of neurosciences, and this debate is still ongoing. This debate is also partially overlapping with the view that effort relies on some depletable metabolic resource, as mentioned in the introduction. “The idea behind ego depletion is that the self’s acts of volition draw on some limited resource, akin to strength or energy and that, therefore, one act of volition will have a detrimental impact on subsequent volition.” (Baumeister et al. 1998, p. 1252) This view, as we said, is disputed and a great number of researchers are adopting the perspective that effort is a motivational issue and can therefore not be depleted such as a finite resource. Roughly speaking, the idea is that “depletion” is nothing other than that another task becomes more attractive than the current one. How does this work?

Inzlicht, Schmeichel and Macrae (2014) explain this by distinguishing between exploration, labour, “have to” or “ought to” goals on the one hand, and exploitation, leisure or “want to” goals on the other. “‘Have-to’ tasks are carried out through a sense of duty, obligation or guilt, whereas ‘want-to’ tasks are carried out because they are personally enjoyable and gratifying.” (Inzlicht et al. 2014, p. 130) Evolutionary pressures led “the organism” to prefer a balance between these two aspects. Depletion is then the “motivated switching of task priorities” when gratification of the different tasks change and other activities may become more rewarding. “Thus, when we suggest that depletion leads to a shift from ‘have-to’ to ‘want-to’ goals, we are suggesting that earlier acts of cognitive effort lead people to prefer activities that they deem enjoyable or gratifying over activities that they feel they ought to do because they correspond to some external pressure or introjected goal.” (Inzlicht et al. 2014, p. 130) But shifts from have-to to want-to goals can be “[…] offset when people become (internally or externally) motivated […]” (p. 130) to pursue have-to goals. Hence depletion does not mean “less motivation overall”, rather, motivation shifts from one “have to” task to a “want to” task and it is this shift in motivation that would explain why performance in a second “have to” task, following a first depleting task gets worse: shifts in motivation bring about shifts in attention, and even shifts in emotion. But this reduction on all

levels of the “have to”-tasks is offset by a corresponding increase at all those levels for the “want-to” tasks.

Kurzban, Duckworth, Kable and Myers (2013) also see an evolutionary pressure playing a role in the “phenomenology of mental effort” (p. 661). They point out that effort is a “subjective experience”, and in particular “the conscious, experienced measurement of the costs – especially the opportunity cost – of continuing the task.” (p. 662) Their key argument is that we cannot apply cognitive control or computational processes as they call it, to several tasks at the same time, we have to “prioritize”. The phenomenology of effort “helps” doing so: effort is an aversive subjective experience, the result of the estimation of opportunity costs, that motivates adaptive behaviour towards another task that yields greater benefits. Hence the costs of mental effort are “located” in the opportunity costs. Said differently, “[…] what, in particular, makes mental tasks feel effortful [is] the expected value of the next-best alternate use of the same computational processes.” (p. 672) Costs are thus encouraging “disengagement” with the task at hand and lead, consequently, to performance reductions. This means that “[…] within-individual changes in performance of mental tasks depend on estimates of their expected utility” (p. 672), estimates which do not always have to be correct (p. 672). They can also be influenced or modified by manipulating people’s beliefs about their expected utility (p. 672). For example, Kurzban et al.’s (2013) account predicts that people who have an interesting alternative to their current task (such as using their smartphone) perform worse than those who do not have such opportunity (p. 672). Hence having attractive alternative tasks within reach means, as Inzlicht et al. (2014) say, that “[…] it is not that people cannot control themselves on some externally mandated task […]; it is that they do not feel like controlling themselves, preferring to indulge instead in a more inherently enjoyable and easier pursuits.” (Inzlicht et al 2014, pp. 130-131). The “feeling” in Kurzban et al.’s sense is the subjective experience of effort that generates this adaptive behaviour.

Shenhav, Musslick, Lieder et al. (2017, p. 108) explain that given "limited information-processing pathways", people engage in a cost-benefit analysis not only to determine which control mechanism to attend to (the "identity" of the control, such as for example to what task relevant aspect people have to turn their attention), but also how much control they invest (the "intensity" of the control, that is how "strongly" they attend to a task relevant aspect). Their view is that given information processing capacities can be applied to many different tasks, it is not that we cannot attend to all of them because of limited control capacities, but it is rather that control limits the attention to some particular tasks to avoid "bottlenecks" or "cross talk" in processing those tasks. The computation of information-processing is indeed a limited "resource", but it is not depletable. They adopt the idea of "bounded rationality" which means, according to Shenhav et al (2017) that "[…] the brain makes optimal use of its finite resources" (p. 107) by calculating the "expected value of control" and attributing control accordingly (Shenhav, Botvinick and Cohen 2013).

Other cost-benefit accounts of mental effort make a direct reference to "economic" decision making. Kool and Botvinick (2014) set up an experiment to test "effort supply" much in line with the economic theory of labour supply that distinguishes between labour and leisure. Cognitive labour is an effortful task that requires cognitive control while cognitive leisure corresponds to what is termed the "default-mode network" that is most active at rest, that is when cognitive control is low (Kool and Botvinick 2014, p. 131). The underlying hypothesis of their experiment is that people do not want either to labour or to leisure, but they prefer a combination of both. How much they will do of both will depend on particular circumstances, notably on the wage or income people receive in exchange for their labour.

In their experiment, cognitive labour and leisure are represented by the same type of task, but with different difficulties. They use the N-back task which consists of looking at a sequence of images of human faces and clicking each time a subject sees an image of a child's face that matches to the one shown "n"-steps earlier. The "labour" task was

a “3-back task”, which requires a lot of attention and memory capacity. Subjects were paid a certain number of candies per trial of the labour task (and not per accurate responses in that task). The unpaid “leisure” task was a “0-back task”, which meant clicking whenever a child face came up and did not require any memory. Subjects could choose between those two tasks as they “preferred”, given their “budget constraint”, which was the time available during which they could execute the tasks (and thus earn more or less “income”). Kool and Botvinick (2014) then test what they say is a typical prediction in economic models: when “wage” per labour-task-trial changes, but subjects are “compensated” for their change in “income” so that they keep the same amount of income at their previously indicated leisure/income choice even after the wage change, then a decrease in wage would increase leisure and vice versa. Economically speaking, by “compensating” for the loss or gain of income due to the wage change, Kool and Botvinick (2014) separate the “substitution effect”, (defined as the effect on consumption of a good due to its price change), from the income effect (which is the change in purchasing power that goes up or down depending on the price change of that good) and focus uniquely on the former. Kool and Botvinick (2014) hypothesis may sound contradictory, but it is actually the consequence of the “substitution effect” which implies – by definition[h] – that if the price of a good goes up (down), people will consume less (more) of it. In modern economics, the price for leisure is its “opportunity cost”, that is, what a person could have done instead of “leisuring” – and this is “working”. Hence the price for leisure is the forgone wage that could have been earned. Thus, if wages go down (up), leisure becomes cheaper (more

[h] Kool and Botvinick (2014) state that “Labor supply theory *predicts* interesting, nonintuitive shifts in choice behavior with variations in wage” (p. 132, our italics). This is false insofar as there is no *prediction* of any change in behaviour, the change is given by *definition*.

expensive) and people will choose more (less) of it. Kool and Botvinick (2014) are happy to report that this is exactly what they observe.[i]

Another "revealed preference procedure" is proposed by Westbrook, Kester and Braver (2013). They present what they call a "cognitive effort discounting paradigm" to learn about the "subjective value of cognitive effort". This paradigm is a "bracketing" procedure that offers experimental subjects a series of binary choices between the lowest difficulty level of a memory task (a N-back task with letters, with difficulty levels from a 1-back, the easiest level up to a 6-back, the most difficult one) and a higher difficulty level in order to find at which payment subjects would just be indifferent between a higher difficulty level for more money and the low difficulty level for less money. The difference in payment between the lower and higher difficulty level is said to be representing the subjective cost of engaging in the more difficult task. Westbrook et al. (2013) observe that as the difficulty level increases, and with it, assumingly, the cognitive effort, the difference in payment between the higher and lower difficulty level

[i] Kool and Botvinick (2014) add that similarly to other experiments, their study also reveals a "demand-avoidance effect" (p. 138), that is to say: when subjects have to choose between two tasks with different levels of cognitive demand, the lower cognitive demand task is favoured because "exertion of executive control is intrinsically costly or aversive". This conclusion, however, is surprising for economists: Kool and Botvinick (2014) not only reveal a particular preference for some leisure/candy bundle under different relative prices, they also deduce from those choices a cognitive demand avoidance. However, in their experiment, people's choices simply conform to a substitution effect, which according to economic theory is the same whenever relative prices change, whether it is a choice between apple and pears or between high and low cognitive demand. It is therefore not quite clear how they spot the demand avoidance effect in addition to the simple working of the substitution effect. If there would be such an effect then this would imply that when prices of pears go up and people buy more apples, we see a pear demand avoidance effect too in addition to the substitution effect. Economists have not yet spotted such an effect.

becomes larger. That is, higher levels of difficulty which correspond to greater use of memory capacity are seemingly more costly to individuals in comparison to lower levels of difficulty. This is equivalent to saying that the subjective value of higher effort tasks is diminishing, that is, subjects "discount" the reward they receive for it more and more. Hence, the subjective value of effort is the reward for the task minus the cost of effort and subjects value the task less the higher the difficulty level. Westbrook et al. (2013) thus conclude that "[…] people are cognitive misers: they are willing to forgo substantial reward to conserve cognitive effort" and that "[…] individuals are biased to avoid cognitive demand" (p. 7).[j] However, one could also paraphrase Inzlicht et al (2014) cited above and argue that rather than being cognitive misers, it seems that people do not "feel like engaging" in a higher level N-back task if it is not sufficiently well compensated. Interestingly, Westbrook et al (2013) replicate the same discounting procedure with a higher fixed amount for the more difficult task and find that subjects discounted larger offers to a lesser extent. Why is effort seemingly less effortful with higher payments? That is, why would people discount effort less if it is paid more in comparison to a situation in which they are paid less? If there is any "bias" at all, then it would be in the change of the discount rate from low payments to high payments, but not in the fact that people trade effort against payments, given their preferences.[k]

[j] Again, for economists it is difficult to see where the *bias* lies, or from where they deduce this information when we simply see people making trade-offs between effort in exchange for some payment. Economists would call this a rational response based on their preferences and not a bias.

[k] What is and what is not a bias is a decision we scientists make with reference to a normative model of a rational (and quite unrealistic) decision maker. Without such a reference point in mind, it is much less clear what a bias really is.

As we see with this brief (and clearly incomplete) overview over neuroeconomic discussions on effort, there are indeed ways to open the black-box of effort and study the modulating "force" that is required to achieve particular goals. Studies on cognitive control can help us understand what happens, cognitively and neurologically speaking, when people do certain specific tasks with more or less "effort". It is this control that can visibly be influenced by incentives and rewards, but whether those incentives also produce unanimously better results may need to be studied in more detail. Reward may also cause some cognitively salient aspects in solving a task to interfere with other aspects of the task that have not been made salient through incentives. Another important point are strategies: people use, more or less consciously, particular strategies to solve their tasks. As far as we have seen, the more recent literature on cognitive control or control strategies are not referring in any great detail to the older literature on cognitive learning and strategy instructions (e.g. Pressley and Brainerd 1985), although they seem to be key for effective cognitive control. In the more recent literature, notably on motivating cognitive control, people simply appear to be substitutable hardware in which their brain works. Reward, so it seems, has a direct impact on the brain, unmodulated by the person. Hence the question is whether the observed changes are the outcome of direct reward-brain connections, or the outcome of a change in how the person, endowed with particular "preferences" and metacognitions, has decided to solve the task? That is, are changes in cognitive control modulated by people's conscious decisions to change their solution strategy? In other words, are incentives changing the way people solve certain tasks (and this may cause a reward-saliency at the expense of other aspects of a task)?

This brief review shows that incentives may be misaligned with the objectives or the complexity of a task. On a behavioural level, this particular insight is something that economists have figured out some 30 years ago, as we briefly will see in the next section: payments must be incentive-proof, so that it is in the interest of the "agent" to execute a certain task as expected by the "principal". The next section will show that it may be insightful to look at principal agent-models rather than to propose simplistic

models of effort supply or cost-benefit calculations that are reminiscent of Robinson Crusoe economics that can be found in introductory microeconomic textbooks (see e.g. Varian 2010, chapter 32). At least this is the feeling that the we have. Said otherwise, the economics of the neuro-economic approach to effort is *not* particularly insightful for economists when economic concepts are used, yet the cognitive and neurological aspects are offering new and interesting perspectives that may change how effort can be understood.

The next section therefore looks at the economic account of effort in its contemporary form, but we will also look at the closely related discussion on labour that was particularly vivid and insightful in the early years of neoclassical economics. In fact, it seems that the area of research where we can learn the most about effort is neither modern economics, nor the economic account of effort in neuroeconomics, but the history of economic thought.

3 Economic studies of effort and labour

"Labour" or "work" has always been a key issue in economic theories. In that sense, economics was always concerned with questions of effort. In earlier writings though, the word "effort" appeared much less frequently than in the more recent economic theory. Classical and earlier neoclassical economists talk about the "toil and trouble" to use Adam Smith's well-known terms, or of the irksomeness and tediousness of work that people had to put up with, as well as about people's laboriousness, industriousness and diligence, and its contrary, their sloth, idleness and laziness (see e.g. De Vries 1994, Konyndyk De Young 2014, Litvine 2014). This language has been reduced in contemporary theories to "effort", and one may say for two reasons: first, an impoverishment in the understanding of what "labour" actually is and does for and with people, and second, the introduction of the idea that monetary incentives modulate the "amount of work" that can be done during the time for which a worker is

being hired. In the following, we will give a rough overview over some important debates on "labour" and "effort" with a few back and forth in the history of economic thought. It turns out that how we think about effort and labour is not only an empirical question, but also a methodological choice and, to a considerable extent, socially constructed. This is also why some important implications about effort, such as for example the meaning of the "law of least effort" is not (yet) properly investigated in economics.

The contemporary economic literature on effort can be said to start with Harvey Leibenstein's "Theory of Underemployment in Densely Populated Backward Economies" (1986 [1957]). Observing the agricultural economy of Least Developed Countries (LDCs), he says it is not uncommon "[…] that in some areas the land is cultivated by less than 50 per cent of the labour force used in less developed areas, and yet higher yields are achieved." (p. 23) How can *more* be achieved with a *smaller* labour force? In a situation of excess supply of labour, the common economic idea of supply and demand is, Leibenstein reminds us, that competition would drive down wages toward zero. But "[o]bviously, the possibility of a zero wage cannot be seriously entertained." (p. 26). Thus, to explain those surprising empirical observations, Leibenstein proposes to look at the relationship of wage and productivity. "Simply put, the extent to which labour is maintained will determine to some degree the amount of effort (or units of work) that will be forthcoming. The amount of work that the representative labourer can be expected to perform depends on his energy level, his health, his vitality, etc., which in turn depend on his consumption level (which depends on income level) and, most directly, on the nutritive value of his food intake." (p. 26). Leibenstein thus presupposes a relationship between food intake, energy level and effort, which is at first increasing up to a certain level, after which, any further energy intake will not help increasing effort further. To the contrary, it will start to decline. Effort is thus seen as greater capacity to work that follows almost automatically from a person who has his or her basic physical and nutritional needs covered.

In the subsequent literature, economists refer to Leibenstein as the first one to have conceptualised what was then to be called "efficiency wages" (see e.g. Akerlof and Yellen 1986, p. 2). Leibenstein's contribution was to introduce a conceptual distinction "[…] between the supply of labour-time (that is, man-hours or man-years) and the supply of work (or effort)" (Leibenstein 1986 [1957], p. 30). This insight brought along a new dimension: so far, economists were concerned with the allocation of "labour" across the economy. The question was who went to work where for which market-wage. Now the question also became how much effort did people "supply" once they were hired. Before Leibenstein, Karl Marx came notoriously close to this idea when he argued that the capitalists had to exert power to extract labour power from workers when they bought their labour time (1889, chapter 6). But contrary to Leibenstein's contribution, the distinction between labour power and labour was not picked up by the "mainstream". In later writings, Leibenstein (1966, 1973, 1978) developed the notion of X-inefficiency in production processes to indicate more generally "[…] the extent to which a given set of inputs do not get to be combined in such a way so as to lead to maximum output." (Leibenstein 1973, p. 766) Labour is obviously an input into the production process and motivation, or actually the lack of appropriate tools to enhance motivation in production processes plays a great role in X-inefficiency. Leibenstein thus extended a "metabolic" understanding of effort to a motivational one.

The notion of "efficiency wages" however existed even before Leibenstein (see Bradley 2007), and was actually coined by Alfred Marshall (1890) who meant by this the "[…] earning measured not by the time spend earning them, as in the case of time earnings, or by the output resulting from the work, as in piece-work earnings, but rather by the exertion of skill and efficiency required from the worker." (Book VI, Chapter III). Marshall did not have the modern idea of efficiency wages in mind and thus a modulation of the individual "supply of effort" as Leibenstein called it, but thought about efficiency in an "objective" sense, that is how "efficient" people could produce things, given their knowledge, experience, social environment, machinery, technological advancement etc. If two persons work under the same conditions and

with equally good technology, then equal piece-rate payments would correspond to their efficiency-earnings. However, if their technology differs, and one person is working in a "cotton mill with an old-fashioned machinery", and the other in one with machinery that had the latest improvements, Marshall's view was that piece-rate earnings could not be the same in a perfectly competitive market. Instead, they had to be higher in the mill with the *old*-fashioned machinery, so that at the market equilibrium, the efficiency-earnings of those two persons were equalized. Hence clearly, efficiency was seen here from a productive side, and not from a motivational side.

Marshall however spotted the motivational side too because he thought that the idea of "the efficiency of the workers" was ambiguous: it would not only be referring to the quantity and quality of the work done by a person, but also to some more "general industrial efficiency" (Book VI, Chapter III). By industrial efficiency, Marshall meant "the conditions on which depend health and strength, physical, mental and moral." (Book IV, Chapter V). The term "Industrial" refers here to "industry" in the older sense of industriousness, diligence and hard work, or effort, as we call it today. He thus says: "Although the power of sustaining great muscular exertion seems to rest on constitutional strength and other physical conditions, yet even it depends also on force of will, and strength of character. Energy of this kind, which may perhaps be taken to be the strength of the man, as distinguished from that of his body, is moral rather than physical; but yet it depends on the physical condition of nervous strength. This strength of the man himself, this resolution, energy and self-mastery, or in short this "vigour" is the source of all progress […]" (Book IV, Chapter V).

"Vigour", however, Marshall writes, "[…] works itself out in so many forms, that no simple measure of it is possible. But we are all of us constantly estimating vigour and thinking of one person as having more 'backbone,' more 'stuff in him,' or as being 'a stronger man' than another." (Book IV, Chapter V) This vigour will depend on a number of factors to which Marshall counts "climat" – he assumes that colder climates

are better for vigour; the quality and quantity of "food", which differs depending on the work one does; and "clothing, houseroom and firing". "When they are deficient, the mind becomes torpid, and ultimately the physical constitution is undermined." (Book IV, Chapter V) But this is not everything there is to industrial efficiency – or "effort": Marshall adds "rest" to avoid "overwork", every other aspect which "lowers vitality", such as "anxiety, worry and excessive mental strain". Finally, he counts "three close allied conditions to vigour, namely hopefulness, freedom and change" as additional factors that influence efficiency: "All history is full of the record of inefficiency caused in varying degrees by slavery, serfdom, and other forms of civil and political oppression and repression." (Book IV, Chapter V)

Marshall's considerations on the conditions for "industriousness" were extremely rich and comprehensive, but he just did not make (or did not spot) the observation that Leibenstein made in relation to LDCs, namely that less can be more: fewer people working (for higher wages) produce more than more people working (for lower wages). Leibenstein, as we saw above, did put it down to nutrition (at least in the LDC context). This idea was also taken up by other economists such as Joseph Stiglitz (1976) when he presented an upward sloping S-shaped "efficiency wage curve", with the level of wages on the x-axis and efficiency level indicated on the y-axis: "There is a region of increasing returns, whereas the individual is brought above the 'starvation' level additional increments in wages result in increasing increments in efficiency, although eventually diminishing returns set in." (p. 187) If we reverse the axes, Stiglitz says, another interpretation of the efficiency wage curve is possible, the wage-requirement curve: "[…] the wage required to obtain a given number of efficiency units from an individual. " (p. 187). The efficiency wage is then the minimised cost per efficiency unit, that is the "minimum food requirement" for obtaining a given number of efficiency units.

It is Robert Solow (1986 [1979]) who is being credited for giving a theoretical intuition of efficiency wages. A transcription of Solow's result by Yellen (1984) who assumes a

production function that depends on the number of employees and effort "e" per worker, which itself depends on wages ($e=e(w)$), states what has become a widely known definition of efficiency wages: "[a] profit-maximizing firm which can hire all the labour it wants at the wage it chooses to offer, will offer a real wage w^*, which satisfies the condition that the elasticity of effort with respect to the wage is unity" (p. 200). This means that a firm will hire up to the point where an additional unit of effort produces a marginal product that is equal to the real wage w^*, the efficiency wage. Given that efficiency wages generally lie above the competitive labour market wages, the labour market will be in a disequilibrium: only some workers can be hired at a greater than competitive price, whereas others would like to work, even at a lower wage, but cannot find a job. A cost minimising firm has no interest in lowering its wage to employ more people, because that would undo the whole advantage of efficiency wages, i.e. that people work at a greater effort level. This means that the typical self-correction mechanism of markets via changes in prices to regulate demand and supply does not hold firms are laying off people rather than changing the wage: wages are "rigid" or "sticky", a notion originally introduced by John Maynard Keynes (1936). Efficiency wages are a macroeconomic explanation of sticky wages.

The idea of efficiency wages thus clearly is pay more and you will get more effort. However, a little excursion into the history of economic thought shows that what we today call a truism is by no means what (political) economists have always assumed. David Spencer (2009) shows that a fundamental idea influenced economic thinking over centuries (and probably since Adam and Eve have been thrown out from paradise): "[o]ne can find in the major periods of economic thought – mercantilist, classical, and neoclassical – a clear emphasis on the negative features of work. The prevailing opinion in mainstream economics has been that work is an inherent 'bad' or 'disutility' that must be bribed from workers." (p. 1) To do so, mercantilist thinkers for example adopted the "utility of poverty" thesis which argued that paying workers more would actually have a detrimental effect on their willingness to work hard (Spencer 2009, chapter 2, see references therein). Workers were considered to be "slothful" and

only want, and penury would make them industrious. Given that they were drawn to leisure, higher payments would only tempt workers to indulge more in their vices, such as drinking excessive amounts of alcohol. Along with this view "[…] was a belief in the prevalence among the poorer sort of a 'target consumption', which fixed their horizons close to subsistence levels, so that the amount of work which they were prepared to undertake was directly linked to the amount of money required to satisfy a basket of basic needs." (Hatcher 1998, p. 69) Hence paying low wages were seen as a convenient tool to ensure that the labouring force did work, but also that it would adopt a virtuous life-style with abstinence and prudence.

The idea of paying higher wages to workers such that they can afford a better standard of living (and thus work better) slowly emerged over time, but this view was not easily adopted. In fact, even economists of the 20th century continued to believe that higher wages would make people work less rather than more. A still widely cited economist, Frank Knight (1921) for example writes:

"It is usual, because superficially "natural" to assume that a man will work more – i.e. work harder or more hours per day – for a higher wage than for a lower one. But a little examination will show that this assumption is for rational behavior incorrect. In so far as men act rationally – i.e., from fixed motives subject to the law of diminishing utility – they will at a higher rate divide their time between wage-earning and non-industrial uses in such a way as to earn *more money*, indeed, but to work *fewer hours*." (p. 117, italics in the text).

Such views continued to use the "work as bad" assumption and saw it therefore as perfectly rational to work less whenever possible. The introduction of the concept of indifference curves finally helped to understand analytically that whether an individual would work more or less depended on the total effect of the wage change, which can be decomposed, as we already mentioned in the previous section, into a substitution effect (which always goes in the opposite direction of the price change) and an income effect (the change in purchasing power, which can be either positive or negative depending

on the wage/price change). The overall effect of a wage change will then depend on the particular "shape" of the indifference curves, that is, on people's preferences, as well as on the sum of those two effects. It can therefore be the case that labour supply at first increases with rising wages but starts to decrease from a certain level of wages onwards. This is now commonly called a "backward-bending" labour supply curve (see e.g. Varian 2010, chapter 9).

It is however worth pointing out that the increase in labour supply was meant in terms of more working hours, but not in terms of greater effort (per working hour). The analysis was supposed to show that if wages increase, people may reduce their leisure time and work more instead. However, even though economists started to be convinced that a greater pay could lead to more work (in terms of working hours), this analysis does not suppose that people "prefer" work over leisure. What people prefer is to have either more money and income to consume, or more time to leisure. The "work as bad" hypothesis continues to persist. But here an important "ontological" change operates. Work is costly because it is what needs to be done to get to income. Work is not done out of interest for a particular activity, it is only a means to earn money and therefore a hindrance, something that consumes time, a sacrifice that people need to accept to get to what they really want. The idea is, as Jeremy Bentham (1871) said: "Men universally desire to enjoy speedily – to enjoy without labour" and "[i]t is this desire that is terrible" (Chpt IX, p. 114).

Moreover, what has gradually changed in economic thought since the mercantilists is the fact that people started to be seen as consumers, as important players in a free-market economy who enjoy having and purchasing goods. That is, people were not any longer seen as ambitionless and wanting to satisfy their most basic needs only. The focus of economic analysis became the allocation of time between leisure and consumption, and not of work (Derobert 2001). "The treatment of work in much economic thought has been premised on a particular view of human motivation and welfare. It has been implied that what matters most to humans is the accumulation of

marketable goods and services, and the increase of leisure hours. Humans are viewed in their role as consumers rather than in their role as workers. Work is reduced to the limited act of acquisition and is not viewed as an activity that can directly influence the life-experiences of people." (Spencer 2011, p. 574)

Working is costly, and nothing else. With the onset of neoclassical economics and marginalist reasoning, the question became what exactly it is that is costly when people work, a debate that became known as the "cost controversy" in economics. On the one side were some economists such as Alfred Marshall, William Stanley Jevons or Francis Ysidro Edgeworth who believed that the cost of labour consisted in the physical and psychological pain and the disagreeableness that it causes, its "toil and trouble", hence its "disutility". On the other side were economists, close to the "Austrian" tradition in economics, who argued that the cost of labour consisted in what cannot be done while working, i.e., in the forgone opportunities. Both sides thought that people tolerate these costs as long as the benefits are at least offsetting them.

The distinction between these two views is best seen in terms of a hypothetical story of a berry picking boy. Alfred Marshall, representative of the first group of economists, writes in his *Principles of Economics* (1890):

"The simplest case of balance or equilibrium between desire and effort is found when a person satisfies one of his wants by his own direct work. When a boy picks blackberries for his own eating, the action of picking is probably itself pleasurable for a while; and for some time longer the pleasure of eating is more than enough to repay the trouble of picking. But after he has eaten a good deal, the desire for more diminishes; while the task of picking begins to cause weariness, which may indeed be a feeling of monotony rather than of fatigue. Equilibrium is reached when at last his eagerness to play and his disinclination for the work of picking counterbalance the desire for eating. The satisfaction which he can get from picking fruit has arrived at its *maximum*: for up to that time every fresh picking has added more to his pleasure than

it has taken away; and after that time any further picking would take away from his pleasure more than it would add." (Marshall 1890, Book V, Chapter II, Paragraph 824).

Hence the cost of labour was the actual subjective experience of doing the task. There comes a point, where labour turns troublesome, weary and unpleasant. Actually, Marshall was among the rare economists who presupposed that labour is not in itself something that people find unconditionally unpleasant (Spencer 2009). The experience of work and the kind of work determines in itself whether people want to do it or not. Marshall (1873 [1925]) makes a distinction between occupation of a gentleman and of a working man. The difference between those occupations are not particular characteristics of the work to be done. For example, one cannot say that the working man is the one who performs some disagreeable duties, "[…] for the surgeon is paid to perform duties most disagreeable." (p. 103). The distinction lies more with "the effect that his work produces on him": if a task tends to give "culture and refinement to his character", it's a gentleman's task, otherwise it is a working man's task (p. 103). The former tasks are most willingly done. "But let us turn our eyes on that darker scene which the lot of unskilled labour presents. Let us look at those vast masses of men who, after long hours of hard and unintellectual toil, are wont to return to their narrow homes with bodies exhausted and with minds dull and sluggish." (p. 105) According to Marshall, it is no wonder that they prefer to rest and to leisure rather than to work. Work is a disutility for them all the time. For others, work becomes a disutility from a certain point onwards, as the berry-picking boy demonstrates.

Frank Knight (1921) is taking the side of the Austrian tradition on the cost controversy and reconsiders Marshall's story some years later:

"Let us take Marshall's example of a boy gathering and eating berries, but with the stipulation that some re-wording would be necessary to make the exposition accurately fit the case of choice between (i.e., combination of) alternatives in a comprehensive, long-time, plan of conduct. We can hardly suppose that the boy goes through such mental operations as drawing curves or making estimates of utility and disutility scales.

What he does, in so far as he deliberates between the alternatives at all, is to consider together, with reference to successive amounts of his "commodity," the utility of each increment against its "cost in effort," and evaluate the net result as either positive or negative, either of a character to prompt the combined action of production and consumption of that unit, or not of this character. The "cost in effort" is evidently in fact the sacrifice of some alternative use or uses of the effort. Even that nondescript conduct called merely idling is still conduct, an alternative motive, and subject to the law of diminishing utility or relative proportions like any other." (Knight 1921, Part II, Chapter III, Paragraph 155).

One of the reasons why it was the latter view on cost that finally has been taken up by mainstream economics is that we are not living in a Robinson-Crusoe economy. Eugen von Böhm-Bawerk's (1894) view was that Marshall's reasoning is correct in the case of people working for themselves, such as Robinson Crusoe. It makes sense to assume that "[…] Crusoe, as a reasonable being, will continue his labour to that quarter of an hour, the disutility of which will be exactly counterbalanced by the utility of the goods produced in this quarter of an hour." (p. 20)[l] Crusoe's wages correspond to the product he produces. Hence the value of his labour is identical to the value of the product, a condition that must be satisfied at the equilibrium. But in a market economy, this condition will in general not hold because the marginal utility of wages for the worker may not correspond to the marginal utility of the product for the final consumer. This

[l] We obviously see parallels here to the cognitive effort discounting paradigm we discussed in the previous section. Westbrook et al.'s (2013) experimental setup seems to "mimic" a Robinson Crusoe one person economy, but overlooks that it is the experimenters who demand subjects to engage in a certain task that they have chosen for them (a Robinson Crusoe subject would probably, alone on an island, never choose to engage in a tedious N-back task), and with a remuneration that is totally ad hoc, no competitive market wage or efficiency wage for that matter.

would only hold under a very particular assumption, namely "[…] that the labourer is entirely free to determine how long he will continue his daily labour. When, however, we turn to the actual facts of our present industrial life, we find […] that this assumption does not obtain […]." (p. 23) In the labour market, where contracts prescribe the number of hours people have to work per week, "[…] the amount of the pain of labour is more or less fixed. When changes occur in the rate of wages or in the value of the product, the labourer is not free to make a corresponding change in the length of his working day and thus restore the equilibrium between utility and disutility." (p. 23). Hence the decision of a person to supply labour cannot be based on the kind of equilibrium that Marshall proposed. If people have to work 10 hours a day, they do it, because it's still better than suffering from hunger. People cannot stop working at the point where the marginal utility of their labour, that is their wage, corresponds to their disutility of working. What is then the decision that applies? Böhm-Bawerk's (1894) article is about the "ultimate standard of value" of goods, but one sees well how this extends to labour supply. People have a great demand for the products of labour and the possession of goods. This "practically unlimited" demand for goods can only be satisfied with "limited labour power" (p. 45) "It is never sufficient to satisfy all our desire; if it was, we would be in paradise; we must, therefore, always choose which of our desires we will gratify. Under the influence of self-interest, we will satisfy them according to the height or amount of the fee which we are willing to pay for their satisfaction." (p. 45) Labour supply will thus depend on our choice which of the desires (or utilities) we want to satisfy. To paraphrase Böhm-Bawerk, it is thus the "utility" of the things we desire that determines labour supply, and not the experienced disutility of labour (over which we have not much influence anyway).[m]

[m] Böhm-Bawerk's sentence is: "It is, therefore, utility and not disutility which, as well on the side of supply as of demand, determine the height of the price." (1894, p. 52). By that he means that the value of a good is not determined by the cost of producing it, i.e. by the amount of labour and "disutility", but

Francis Ysidro Edgeworth (1894) responds to Böhm-Bawerk's critique by saying that his thoughts on the ultimate standard of value are correct – "[…] if the quantity and quality of labour be regarded as fixed." (p. 521) However, Edgeworth says, "[t]he question only is how far variable effort and sacrifices enter into the production of labour." (p. 521) Hence Edgeworth understood that workers may not be able to choose how many hours to work, but that they can decide on the intensity of work. To bring the "disutility" of labour back into the consideration of "labour" supply would therefore perfectly make sense. In Böhm-Bawerk's (1894a) response to Edgeworth, he did not take up this point. It is as if Edgeworth's point about the intensity of effort had fallen out of consideration of mainstream economics for several decades (until Leibenstein 1986[1957]) because it was the Austrian account that became the "mainstream". This was probably the case because of the general attempt within the discipline to drop off "the last vestiges of utility analysis" as Paul Samuelson (1938, p. 62) said a few years later, to make economics more "scientific" and based on observable choices rather than on inaccessible disutilities and subjectivities. The mainstream model of labour supply has become a "labour-less" analysis of consumption opportunities (Derobert 2001, Spencer 2004, 2009). It is a model that decides on how "consumers" allocate their time between consuming and leisuring. It has evacuated any consideration on what people do, what happens to them when they are working, and on what is their subjective experience. The mainstream model abstracts form labour and becomes an official "fiction": "The fiction is that the agent disposes of a potential income R_o obtained by dedicating his entire endowment of time to working, and that he buys leisure and consumer goods using this income. From this point of view, the wage appears to

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uniquely by the "utility" for people who want that good. In the determination of the value of a good, the labour factor (which was an important aspect for classical economists in particular) thus disappears.

correspond equally to the *price* and the *opportunity cost* of leisure [italics in the original]. The solution of the consumer's problem then follows the path of utility optimization subject to the budget constraint. We thus derive the functions of demand for consumer goods and leisure." (Cahuc, Carcillo and Zylberberg 2014, p. 15) Hence if the "consumer" chooses to leisure one hour, instead of working at a given wage, we can deduct the cost of leisure by the forgone wage the person could have earned. And we can also deduce the person's preferences from their choices: if the person chooses to leisure rather than to work, then they must do so because they prefer it.[n] This information is thus easier to access than any account of the inner feelings and subjective experiences of "weariness", "monotony", and "disutility" (or even pleasantness and satisfaction) that labour can cause. Said differently, the phenomenology of working has been excluded from any further analysis. "The point is that "labour" is really the sacrifice of some desirable alternative use of one's time and strength. If there is no alternative there is no sacrifice […]" writes Frank Knight (1921, Part II, Chapter III, Paragraph 155). The cost of labour has become the sacrifice of the "utility" of leisuring, of that thing that one could also have done with one's time, and not the "disutility" of labour as such. Note however that the labour supply model is not an analysis of incentives. It does not analyse if and how the "intensity of working", or

[n] This statement is obviously wrong, and Amartya Sen has pointed this out long time ago (Sen 1973, 1977, 1993). We cannot deduce preferences from choices, only revealed preferences (and this only if certain consistency axioms are satisfied). In contrast to the notion of preferences, the concept of revealed preference does not necessarily indicate any psychological reason why people choose one or the other. People can choose an option for whatever reason, including, for example, because their mother told them to do so. Nevertheless, there is another (unofficial) fiction in economics that persists, namely that revealed preferences correspond to preferences.

of “effort”, varies with greater pay within a given working hour. This analysis will only come with the contemporary use of the notion of “efficiency wages”.

We have seen so far that the idea that greater pay induces more work has not always been the immediate way of seeing things. This intuition evolved over time. It’s quite a history before we come to Solow (1986[1979]) who actually thought that higher wages induce “higher morale or higher quality of personnel” and which therefore translate into greater effort. This is literally at the opposing end of how mercantilists saw it. Today’s economic literature, however, generally assumes that people’s “morals” have little to do with it, but people’s self-interest as long as the benefits exceed or equals the cost of effort. But self-interest in an interpersonal relation, and notably of an agent, working for a principal, takes on a new dimension. When a “principal” or employer hires an agent or employee to work on their behalf, they do not have the same information as the agent. Who the agent is, whether a “quality” person or not, and how much effort that agent puts into doing the tasks for which they were hired is not (immediately) known and easily accessible to the principal. The assumption is that if people are offered a higher wage, they would accept it, but without formal enforcement devices or control mechanisms, they only deliver the minimal amount of effort required. This means that people shirk. This is no moral judgement; it is the rational response (in the economic model) of any individual in such a situation (see Baker 1996 on the genealogy of moral hazard).

With the onset of contract theory, the focus from free market exchanges shifted to the firm as a social – and hierarchical – organisation. Samuel Bowles (1985) referred to the organisation in firms as “[…] neo-Hobbesian because […] the key to understanding the internal structure of the firm is the concept of malfeasance. Also known as shirking or free riding, malfeasance gives rise to the archetypal Hobbesian problem of reconciling self-interested behavior on the part of individuals with collective or group interests. Moreover, the neo-Hobbesian explanation of the functional nature of the hierarchical organization of the modern workplace bears a close resemblance to the

original Hobbesian rationale for the state as a socially necessary form of coercion." (p. 16) This means that a principal who strives for profit maximisation must make sure that the interests of the agent become aligned with those of the principal. Paying incentives will help, but it is not sufficient. Contracts between the principal and the agent must satisfy the "incentive constraint", which means that it must be better for the agent to exert the effort rather than to shirk. Efficiency wages, as we have seen above, are wages that are paid above the competitive market wage to incentivise greater effort. The downside of them is that they come with unemployment. Unemployment is a threat to the agent. If agents are caught shirking and lose the job, it is not sure that they will find another employment immediately. Hence it is advantageous for them not to shirk, the incentive constraint holds. Unemployment acts as a "disciplining device" (Shapiro and Stiglitz 1984). In a world of incomplete information, disciplining devices such as unemployment, or supervision, monitoring and other control devices are necessary – according to economic theory – to ensure that the agent is committed to give their agreed level of effort (see McIntosh 1997, chapter 2 for a review of the earlier "effort" related literature of principal-agent models).

One could think that to control agents, it would be sufficient to set up contracts that specify in advance what the desirable outcomes are. Theoretically, it would be possible to offer variable pay contracts, such as piece rate payments, in which any payment would depend on outcome and thus on effort rather than on a fixed amount of payment or wages per hour. Such contracts would controll the agent's effort and payment will be directly dependent on it. However, in many jobs, the precise nature of the "outcome" cannot easily be determined nor is it clearly measurable. The result of people's effort may not only be dependent on factors outside of their control, but the outcome itself the product of different "strategies" to solve the multiple tasks which a particular job consists of. Economists thus have understood that if payments are made dependent on certain tasks (which may be easier to assess and quantify) but not on others, this can give rise to "[…] dysfunctional behavioral responses, where agents emphasise only those aspects of performance that are rewarded". (Prendergast 1999, p. 8). A known

example is teachers' pay that is dependent on scores of their pupils: if this is the case, teachers may "teach to the test" and disregard other aspects of their job.

Since then, effort has become a human resource used to increase production efficiency. But contrary to other resources, economists do not think that "effort" is a fixed reserve. "It" can be increased or reduced depending on particular circumstances and organisational rules. Over the last decades since Leibenstein, economists have studied (without however referring back to the many pioneering writings of Leibenstein on X-inefficiencies) the underlying general principles and specific institutional details of this "human resource management" and "personnel economics" (Lazear and Shaw 2007). They do so by relying on some key economic assumptions, such as that people are rational and maximising agents, that production efficiency is the goal to attain, and that market-like situations within the firm mimic competitive pressures that can push people to their production frontier. Rather than some base-salary or hourly wages, "pay-for-performance" schemes are now seen as the payment tool to be used whenever possible. And yet, all this has been done without ever understanding what effort "is". Effort remains a "black box". The question of what is and does effort with and to people, what it means to increase or decrease effort to people has never been asked beyond the assumption that it must be in people's interest to do so. There is some literature on job satisfaction and its influence on wellbeing (e.g. Clark and Oswald 1996), but this is not a mainstream topic, because the focus in mainstream economics remains the consumer and producer, not the worker.

4 A theory of activity

In Spencer (2009, p. 81) we read that Alfred Marshall rejected the idea that the theory of consumption was the scientific basis of economics, insisting instead that the job of economists was to develop a "theory of activity". Marshall (1873[1966]) pushed for a society in which all people have "gentleman jobs" which would imply that people live

in conditions where all can enjoy their labour. He writes that "[v]igorous mental faculties imply continual activity. Work, in its best sense, the healthy energetic exercise of faculties, is the aim of life, is life itself […]" (p. 115). The idea of enjoying work however has never been pushed forward in mainstream neoclassical economics, let alone studying the conditions under which labour would be enjoyable. There is arguably a big difference between Marshall's view who sees in work the aim of life and the more generalised view which persisted throughout centuries that people are lazy and do not want to work. Laziness has never been seen as a "revealed preference" in the context of adverse working conditions and tiresome, repetitive activities. It has instead been taken as a character trait of those who work. Modern economic theory has distanced itself from such an explicit judgement of laziness and subsumed instead people's attitude towards work under the general heading of self-interest, which must be constrained and controlled in order to avoid shirking and efficiency losses in production.

The pressing and maybe obvious question of "who wants to work for a profit maximising capitalist?" probably is too Marxist for mainstream economics. But Marx tells an interesting story about early colonial capitalism, which is insightful for the discussion of effort. In chapter 33 of his "Capital", Marx cites the political economists called E.G. Wakefield, an important "empire builder" (Pappe 1951, p. 88) of his time, who observes that in new colonial settlements, a labour market had difficulties to emerge because there were no workers to hire. Marx makes fun of Wakefield, when the latter tells the story of Thomas Peel, a colonial settler who left with a big ship full of machinery as well as workers to establish a new settlement in Australia: "Mr. Peel, [Wakefield] moans, took with him from England to Swan River, West Australia, means of subsistence and of production to the amount of £50,000. Mr. Peel had the foresight to bring with him, besides, 300 persons of the working class, men, women, and children. Once arrived at his destination, "Mr. Peel was left without a servant to make his bed or fetch him water from the river." Unhappy Mr. Peel who provided for everything except the export of English modes of production to Swan River!" (Marx

1889, pp. 791-792) These people, who came to Australia on that ship, discovered that there was enough land for everyone, so they did not have to work for the capitalist. They could survive by cultivating their own land and without selling their labour to someone. Marx thus comments: "Wakefield discovered that in the Colonies, property in money, means of subsistence, machines, and other means of production, does not as yet stamp a man as a capitalist if there be wanting the correlative – the wage-worker, the other man who is compelled to sell himself of his own free-will. He discovered that capital is not a thing, but a social relation between persons, established by the instrumentality of things." (p. 791). What this story thus clearly says is that if people are not compelled to sell "themselves", if they "do not work", this does *not* mean that they do *not want* to work or exert effort as it was assumed throughout much of the history of economic thought. Of course, people work and can engage in great effort to cover their needs and desires, but, as Marx's story tells, people do not necessarily want to work for someone else, or they do not want to do a particular job or task, or to be in a particular kind of social relation. Contemporary mainstream economics has understood that too and takes this resistance to work as a given. But instead of questioning these social relations, it uniquely focuses on how best to "manage" human resources under "neo-Hobbesian" relations (Bowles 1985) and now to align the interests of the agents with those of the principals. But this is clearly just one way of considering effort. It is not a complete picture of effort, which necessitates testing, for example, which social relations or which work conditions work best for "investing" effort.

The neuroeconomic tendency to assume that people are "cognitive misers" (Westbrook et al. 2013, p.1) or that "[…] people generally avoid hard work […]" (Inzlicht, Schmeichel and Macrae 2014, p. 129) is even more surprising as neither the "quality" of the task, nor the social relation behind such effort-avoidance is ever mentioned. The

neuroeconomic literature employs a different optimality principle[o], not maximisation of some self-interested objectives but the "law of least effort" (Hull 1943). But this law is far from stating that people avoid working hard! Rather, the fifteenth corollary in Hull's book "Principles of Behavior" (1943) states: "If two or more behavior sequences, each involving a different amount of energy consumption or work (W), have been equally well reinforced an equal number of times, the organism will gradually learn to choose the less laborious behavior sequence leading to the attainment of the reinforcing state of affairs." (p. 294). This means that if two ways of doing one and the same task are possible, then whatever the organism is (and in particular human beings in certain social relations), it tends to choose the less effortful one. Why should an organism actually choose the more effortful if a less effortful is also available? Is this not a principle of efficiency at its very best? Would not any principal *prefer* that "their" agents choose to do the less effortful rather than the more effortful task of the two to obtain one and the same result and thus to conserve "energy" to do something else as well? In fact, would it not be more appropriate to inquire how to *decrease* effort for particular tasks to *conserve* energy rather than to study the conditions under which people *increase* their effort? Cost minimisation in economics in general means to re-organise a production plan in such a way as to reduce the use of certain inputs and not increase them, why should effort be the exception?

What would it mean to study how to decrease effort? Cognitive and neuroscientific and research give some answer by bringing forward the question of cognitive control and cognitive strategies, i.e. the question of how people actually do solve certain mental tasks. Our own introspection tells us that when we are faced with new tasks, we are trying to find out the best way to solve them, which will require repeated trials,

[o] On the heuristics of different forms of optimality, see Shoemaker (1991).

learning, experimenting and researching, depending on the difficulty level. What will be the best solution? Probably the one which we have learnt to require the least amount of effort, some rule or proceeding that will help us to solve the task as efficiently and as successful as possible within a given time.

The interesting question of effort therefore, it seems, is to minimise it and thus to learn about efficient ways of solving a task. This means that it is necessary to understand how people work, how they solve tasks, what their techniques are to reduce effort, their tricks, astuteness and sharpness of figuring out how a task "works best". Said differently, while it is important to study the conditions and set-up of work, i.e. the ecological conditions of work, it is equally important to study the ergonomics of work, that is, what are the best (cognitive) work processes or strategies to solve a task. Following this line of cognitive and neuroscientific research is thus an interesting and novel form of knowledge for economists to open the black box of effort and to reconsider all the assumptions that come along with it.

So far, most of the neuroeconomic research of effort reviewed in this paper has not gone down that route but has adopted standard economic concepts to tell "as if" stories about computations that happen in the brain. Even more so, this neuroeconomic research uses the idea of cost-benefit calculation, thereby talking of "disutility" and "opportunity cost" as if these concepts can be interchangeably used, thus disregarding the insights of the history of economic thought and the debate around the "cost-controversy" as it happened in the late 19th and early 20th century. When Kurzban et al (2013) for example write: "Subjective effort, on this view, is the conscious, experienced measurement of the cost – especially the opportunity cost – of continuing the task" (p. 662), then they mix up two concepts of cost that are well separated in economic theory. The point of opportunity cost in economics was exactly to get rid of subjective experiences and not to equate it with them. Opportunity cost, in economics, is the foregone "utility" of some other activity, and not any experienced "disutility". What is foregone, that is, not done, cannot be experienced. What may be experienced

is something else, such as the regret, or relief, of not having done this other activity. But this then would not be effort. Opportunity cost has been introduced into economics as a convenient "fiction" to be able to measure costs (the foregone market wages or other payments a worker could have earned instead of leisuring). It is not quite clear how the brain computes forgone costs of not employing some of its mental capacities, whether there is an internal market in the brain that signals possible "prices" of doing one or the other task. Instead of engaging in such speculation, it may be more interesting to reconsider the early neoclassical debate on the cost controversy and choose the "road not taken", i.e. to reside with Jevons, Marshall, Edgeworth and others, who contemplated in more detail the actual experiences of working. Another interesting avenue would be to introduce more mainstream insights of principal-agent models, and most notably the idea of incomplete contracts. This means that rewarding certain activities may have the tendency to highlight certain cognitive mechanisms at the expense of others, such as we have seen in some of the neuroscientific studies we discussed above (Krebs et al 2010, Padmala and Pessoa 2011). Yet this again points towards the importance of studying the ergonomics of cognitive tasks, instead of focussing on incentivising greater effort only, which may have some unexpected behavioural and cognitive consequences.

Thorsten Veblen (1898) argues that the view of the "irksomeness of labour" has evolved as a social convention over time. Humankind would be quite alone among all the different species of animals in complying with this "axiom", Veblen says, which is to want the goods produced by labour, but to avoid the labour to produce them (p.187). He writes that "[u]nder the selective process through which species are held to have emerged and gained their stability there is no chance for the survival of a species gifted with such an aversion to the furtherance of its own life process." (p. 187). For Veblen, the view emerged because the behaviour of "sportsmanship" came to dominate the instinct of "workmanship". Predatory and competitive "exploit" became a cultural value and with it the demand for leisure and the exhibition of conspicuous wealth. This means that certain kinds of effort, and in particular useful effort, effort that leads to

useful products became repudiated, while other types of effort, such as “sports and similar employments” (p. 188) that delivered no useful products, were more highly regarded. Is it that neuroeconomic and economic researchers adopted such a “reinforced” and conventional way of thinking about effort without engaging in a wider reflection on the condition under which effort is exerted? Opening the black box of effort seems to be more important than ever. If this is done, neuro-economic research will help to conceive an interesting “theory of activity” as the economist Alfred Marshall was the first to attempt.

Chapter 1

The general introduction situated the neuroeconomic approaches to cognitive effort within a broader conceptual and historical frame, highlighting their relevance for understanding the cognitive processes behind cognitive effort. In the first chapter, we systematically describe and elaborate on the main neuroeconomic approaches to cognitive effort. We examine the core empirical findings and theoretical insights associated with each approach, paying particular attention to their foundational assumptions and methodological strategies. Furthermore, we identify the central research questions that guide each framework, delineating the specific aspects of cognitive effort they seek to explain—such as why we exert effort and how it is exerted. We identified to approaches under which we can categorize most of the work, acknowledging overlaps. This chapter thus provides a structured map of the neuroeconomic landscape of cognitive effort, laying the groundwork for the experiment presented in the subsequent chapter.

Two Frameworks for Cognitive effort: Arousal and Valence

Abstract

Research on cognitive effort has produced a vast scientific literature. In this paper, we propose a roadmap to describe key developments over the past 70 years. We highlight a shift from prioritizing asking, “What happens when we engage in effort?” to “Why do we engage in effort?”. The first question generates a research framework that we call the arousal framework, where effort is seen as a state of increased physiological activation. Research within this framework has flourished following the discovery of the ascending reticular activating system and has focused. on the role of locus coeruleus-noradrenergic pathway in modulating the intensity of cognitive control. The second question has been central to research driven by neuroeconomics and advances in brain imaging and computational neuroscience, leading to what we call the valence framework. In this perspective effort is considered inherently aversive, and it is assumed that individuals engage in effort only if the benefits outweigh the costs. Within this framework, research seeks the neural correlates of expected value of cognitive control with a spotlight on basal ganglia-prefrontal dopaminergic pathways. We describe exemplar work pertaining to each framework, highlighting their key epistemological features. We argue that future research on cognitive effort should understand the complementarity and interaction between valence and arousal, integrating the two questions of “what happens” and “why”. We also argue that the understanding effort requires to look more specifically into how people are executing tasks, that is which solution strategies people come up with when they engage in cognitively demanding tasks.

1-1 Introduction

Cognitive effort, also named mental effort, has intrigued scientists for well over a century. The experiments from Angelo Mosso in 1882, using a finely balanced wooden table designed to detect changes in cerebral blood during cognitive activities of increasing complexity, can be considered as an early attempt to associate mental effort with measurable physiological changes (Sandrone et al., 2014). Nearly 150 years later, fundamental questions—such as what cognitive effort is and how to measure it—remain central to a thriving and complex field of research.

Effort has been extensively studied in various contexts, including pathologies such as depression, schizophrenia and attention deficits (Cléry-Melin et al., 2011, Culbreth et al., 2018), but also in the context of cognitive learning and education (e.g. Dweck, 2006; Pressley and Brainerd 1985). It is only in the past two decades, however, that cognitive effort has begun to be considered as a subject of study in its own right (e.g. Kurzban, 2016).

This paper showcases some key developments in the scientific understanding of effort, with a focus on research since the 1960s. Over this period, a notable shift has occurred in the primary research question: from asking, *"What happens when we engage in effort?"* to *"Why do we engage in effort?"*. This shift can be attributed to the growing influence of neuroeconomic analysis, which is based on the assumption that economic behavior involves cost reduction and reward seeking. This evolution in research approaches has unfolded alongside paradigmatic and methodological advancements and trends, including the discovery of the reticular ascending system, deeper insights into neurotransmission pathways, and broadly the development of system neuroscience, as well as the expansion of neuroimaging and computational neuroscience.

The first question is grounded in what we term the arousal perspective of effort, which conceptualizes effort as a state of increased physiological activation, ranging from quiet

(for low effort) to active (for high effort), directed to a specific cognitive activity. In experimental setups, effort is measured through variations in physiological indicators such as pupil size, skin conductance and heart rate variability, typically recorded continuously, in a second-by-second experimental design (e.g. Kahneman, 1973).

The second question reflects what we term the (negative) valence perspective, which considers effort to be inherently aversive and unpleasant, varying from low aversiveness (low effort) to high aversiveness (high effort). This approach explicitly rejects the view that arousal is to be equated with effort on the basis that arousal only constitutes an unspecific measure of effort (Westbrook et al 2015, p. 398). Instead, their view is that effort relates to a cost that individuals aim to minimize as much as possible to fulfil a determined goal or task demand. That is, if two or more ways to do something are available, the assumption is that individuals will choose the one that is the least costly. Experimental studies using a discrete evaluation of effort, in block-based (or trial-by-trial) designs investigate which task or effort level participants choose and/or at which intensity and duration. According to the valence perspective, people engage in effortful activities only as long as the perceived benefits or rewards outweigh the costs. These costs may stem from the aversiveness and unpleasantness of effort itself (e.g., Westbrook et al. 2015) or, more indirectly, because the aversiveness of effort signals opportunity costs that reflect the forgone benefits of an alternative activity that could have been pursued instead (Kurzban et al 2013). This perspective proposes to quantify effort as a subjective value understood as the amount of money, or other form of reward, required for an individual to be indifferent between a low-effort, low-reward task and a high-effort task with a greater reward.

The arousal perspective relates to the question of selective attention, which is understood as a limited capacity distributed across different tasks. However, this perspective does not clearly define what this capacity consists of, nor how attention is allocated between tasks (Kahneman, 1973; Bruya & Tang, 2018). The valence perspective of effort can readily account for why individuals persist in or switch

between tasks based on cost-benefit calculations, but it encounters a challenge known as the effort paradox (Inzlicht et al., 2018): if effort is inherently aversive, why do people – even when given a choice – engage voluntarily in cognitively demanding activities such as, as Inzlicht and colleagues (2018) ask "[…] learning how to play and master the latest video game, or sticking to an unpleasant diet", or simply "[…] the effort that comes from merely thinking things through" (p. 337)? Stated differently, if people engage in effortful activities only if the cost of doing them will be offset by some benefit or reward, then a number of tasks that we need to do would possibly never been done.

To address the limitations of each perspective, we propose considering their guiding questions as complementary. Understanding what occurs during the exertion of effort may shed light on why effort is exerted, and *vice versa*. More specifically, by complementarity we mean to consider the motivational dimension of effort, its valence, together with its physiological arousal component. That is, it is not a question of considering effort as being explained either by the valence or the arousal approach, but to study the relation and interaction between arousal and valence. Of course, there are papers that adopt the valence perspective which also account for physiological data (e.g. Botvinick & Rosen, 2008; Kurniawan et al., 2021; Reddy et al., 2018; Chevalier et al 2018; Clay et al 2022); yet they often attach a different explanatory value to these measures cantered on the decision-making processes rather than on effort exertion itself. Additionally, we introduce a third question: "how is effort executed?" This concerns the selection of strategies or methods used to solve a given task. By strategies we mean the concrete and complete instruction of how to solve the task. Both perspectives acknowledge that multiple strategies may exist for the same task, yet experimental setups rarely control for them when measuring effort: they tell individuals what to do during an experiment, but do not regularly instruct them as to how to solve the task. Our view is that solution strategies depend on a particular plan or design of cognitive and learning mechanisms. Not controlling for the strategy people use when solving a task means remaining agnostic about what they exactly do. It is

therefore difficult to fully understand effort if we do not also consider also what people actually do when they engage in effortful tasks and how, for example, what they do may be changed with varying rewards.

In the next section, we begin with a discussion of the arousal perspective, focusing in particular on Kahneman's well-known book "Attention and Effort" to highlight key elements of this approach (Section 2). We then examine studies that have attempted to clarify the concept of limited capacity or resources — an idea introduced by Kahneman, but which has remained conceptually and empirically unclear (Section 3). Next, we explore the valence perspective which is a response to shortcomings of limited-resource-based approaches, notably one that sees resources in metabolic terms (Baumeister et al., 1998) (Section 4). Finally, we highlight and discuss the conceptual advantages and limitations of both approaches and outline directions for future research (Section 5).

This paper is not intended as a comprehensive review of the literature on cognitive effort. Rather, it aims to trace some recent historical development of the concept of cognitive effort. We argue that the valence perspective may have disregarded the arousal perspective too quickly. To subsume all decisions on effort to some economic cost-benefit calculus – which in itself is not observable – may overlook other important processes and mechanisms that equally affect performance. We therefore appeal to a renewed interaction between these two perspectives, to which however we add the specific question of studying how people solve particular tasks.

1-2 Arousal framework

Daniel Kahneman's monograph *Attention and Effort* (1973) is still a major reference in relation to arousal-related studies of intentional effort. In the book he revises previous research on attention and proposes his own view, based on collaborative

studies from his early career. Our view is that Kahneman raises important issues that still are relevant for today's research on cognitive effort and are thus worthwhile to be considered in more detail.

Kahneman proposes an alternative theory to structural models of attention (Broadbent, 1958; Deutsch & Deutsch, 1963). These models assume that we cannot process two or more stimuli simultaneously when they rely on the same response mechanism. A "bottleneck" occurs, necessitating some form of selection among stimuli that could occur at different stages in the processing stream from sensation to perception. This bottleneck thus limits cognitive activity. In contrast, Kahneman argues that cognitive operations are more flexible and adaptive: rather than a rigid bottleneck, attention has a limited capacity, but which can be allocated with some degree of flexibility among concurrent activities and is responsive to different processing demands. For instance, a taxi driver can engage in conversation with a passenger while driving but may interrupt the discussion when executing a particularly complex turn. Our capacity to pay attention is influenced by what Kahneman calls "enduring dispositions" (e.g., p. 4) but is also malleable, adapting dynamically to varying attentional demands. As a "crude" metaphor for his capacity model, Kahneman likens attention to an electricity supply: total power output flexibly adjusts to the number of machines in use, albeit within a fixed limit (p. 14).

Kahneman builds on Berlyne (1960), who observed that the intensity of attention is linked to arousal. Arousal refers to the organism's global physiological and psychological state, ranging from deep sleep to wakefulness and hyper alertness (see Gazzaniga et al., 2019, p277). It is associated with physiological markers that can be objectively measured, such as heart rate variability (Fairclough & Houston, 2004; Gendolla et al., 2012; Hess & Ennis, 2011), skin conductance (Naccache et al., 2005; Venables & Fairclough, 2009), and pupil dilation (for a review, see Van der Wel, 2018). A major landmark in the history of neuroscience was the discovery of the reticular activating system, a collection of nuclei in the pons whose diffuse projections to the

cortex regulate arousal level. Berlyne (1960) relies on this work to provide a neurophysiological foundation of his theory of how attention is allocated across stimuli. While he focused on how stimuli attract attention automatically due to their intrinsic properties, like novelty or complexity, Kahneman extended this framework to voluntary attention, introducing an important distinction: people do not only attend to stimuli because they are arousing but also because they are relevant to the execution of a task. This is where effort comes into play—effort corresponds to arousal when we voluntarily engage in activities. Effort-arousal is thus conceptually distinct from alertness, which results from involuntary reactions to stimuli. For Kahneman, concepts such as "investing capacity," "exerting effort," and "paying attention" are synonymous and closely linked to arousal (p. 8). He writes: "In its physiological manifestations, effort is a special case of arousal, but there is a difference between effort and other varieties of arousal, such as those produced by drugs or loud noises: the effort that a subject invests at any one time corresponds to what he is doing, rather than to what is happening to him" (p. 4). Kahneman thus defines effort as the intensity of voluntary attention dedicated to activities selected based on a person's current plans and intentions (p. 4). Throughout this text, when referring to arousal-based effort, we mean this voluntary, goal-directed investment of attention. The individual "allocation policy" is shaped by the subjective relevance of tasks and the selection of actions to fulfil certain intentions and plans.

A consequence of linking effort to arousal is that effort can be indexed by physiological markers of arousal like fluctuations in autonomic nervous system activity. Hess and Polt (1964) were the first to report that pupil dilation increases with cognitive effort, such as when solving difficult mental arithmetic problems. Later experiments confirmed this finding, including one by Kahneman and Beatty (1966), which showed that remembering a string of digits leads to a proportional increase in pupil size with each additional digit. Based on this, Kahneman suggests that physiological variables, such as pupil size, provide a useful second-by-second measure of exerted effort. This has two important consequences. First, effort can be operationalized by tracking

changes in these physiological markers during cognitive activity. Second, the phenomenology of effort is shaped by the modulation of arousal and its associated physiological sensations.

Kahneman (1973) argues that one cannot exert more effort than is necessary to complete a task that one already knows how to perform (p. 14). Once a task is selected, the required effort is task-dependent rather than discretionary. As such, the major determinant of effort-arousal is task difficulty, not voluntary decision (p. 15). Effort varies in tandem with arousal, increasing as task difficulty rises. However, heightened arousal also narrows attentional focus (e.g., Easterbrook 1959, Cue utilization theory), restricting the number of cues considered when solving a task. This can negatively impact performance, especially in complex tasks requiring broad information processing. This phenomenon is captured by the Yerkes-Dodson law, which posits that performance is optimal at moderate levels of arousal but declines with both low and excessive arousal (Yerkes & Dodson, 1908; Hebb, 1955). Too little arousal leads to inattention and poor engagement, while too much arousal may not only alter how tasks are performed—by emphasizing fewer cues—but also affect the speed-accuracy trade-off, leading to increased errors as responses become faster at the expense of precision (Posner et al., 1973).

Another explanation for performance decline with increased effort is "capacity interference," which Kahneman distinguishes from "structural interference." Structural interference occurs when two activities compete for the same response system, such as processing different auditory streams whispered into each ear simultaneously, which necessitates selective attention. Capacity interference, on the other hand, arises when the combined effort demands of multiple tasks exceed available cognitive resources. Up to a certain point, attention can be flexibly distributed among concurrent tasks, but as task difficulty increases, cognitive capacity may become overloaded. Before the system reaches a "breaking point," certain tasks will be prioritized, while others are either abandoned or delayed (Kahneman, 1973, p. 201).

Kahneman refers to this drop in performance as “deficit”. This deficit can be measured for example in the subsidiary-task design introduced by Brown (e.g. 1964). Subjects are instructed to perform a primary task as well as they can and to devote only the remaining capacity to another task. The quality of performance of this subsidiary task provides a measure of the effort required by the primary task. Increasing or decreasing the difficulty level of the primary or the subsidiary task informs on their mutual influence. Hence increasing the difficulty of the primary task may lead to a drop of performance of a subsidiary task – due to interference between tasks – and this drop in performance represents a deficit – or a cost – relative to the performance of an easier primary task. This highlights the importance of the “choice of the processing mode of tasks” (Kahneman, 1973, p. 201), which refers to how tasks are approached and solved—a concept we term “solution strategies” in this paper.

Kahneman effort-arousal framework has found echo over the years in several subsequent theories on attention, as well as on theories of cognitive control in general. For example, extensive work has specified the role of the locus coeruleus – a nucleus part of the reticular activating system source of cortical noradrenalin that regulates arousal – in cognitive control (Aston-Jones and Cohen 2005), attention (Aston-Jones et al., 2000) and effort regulation (Bornet and Bourret 2021; Grueschow et al 2020). Sara and Bouret (2012). This body of work also highlights the crucial role of top-down pathways coming from higher cognitive areas in the prefrontal cortex to the locus coeruleus in directing attention toward task-relevant stimuli. This top-down arousal mechanism is distinct from the bottom-up pathways, which are triggered by salient stimuli that can evoke stress or fear responses. Kahneman’s effort-arousal framework has not been without criticism, however, as Westbrook and Braver (2015, p. 398) note, “Though sympathetic arousal may accompany cognitive effort, it also responds to numerous other processes that are unrelated to effort. For this reason, […] arousal may provide evidence of effort, but it should not be equated with cognitive effort.” Kahneman (1973) acknowledges this, warning that arousal can be confounded with stress or anxiety (p. 24). This concern may have contributed to the diminished

adoption of the arousal-based effort model. Further exploration into this distinction could refine our understanding of effort as voluntary attention investment rather than abandoning the concept altogether.

In the following sections, we further examine the historical development of psychological theories of effort and explore why focus has shifted from the arousal-based account towards what we term the valence-account of cognitive effort.

1-3 From Arousal to Valence

The arousal perspective of effort is deeply rooted in psychophysiological theories of attention. It posits a limited capacity that necessitates selection, though the exact nature of this capacity or resource is not explicitly explained by the research discussed so far. To address this question, Baumeister et al. (1998) tested the hypothesis that top-down, goal-directed processes governing attention allocation rely on a finite resource. Their experiment marked a pivotal shift in the study of effort, moving from second-by-second online observations of effort exertion to trial-by-trial experimental designs that examined discrete task selection.

In Baumeister et al.'s experiment, participants were presented with two dishes: one containing radishes, considered healthy but not particularly appetizing, and the other filled with chocolates, which were delicious but less healthy. Participants were divided into three groups: one was instructed to eat only radishes, another only chocolates, and the third could eat both. They were then asked to solve an unsolvable puzzle. The radish-only group withdrew after an average of five minutes, whereas the chocolate group persisted for 18 minutes, and the unrestricted group lasted 21 minutes. These results suggested that resisting the temptation to eat chocolates "depleted" participants' resources, leaving them with less capacity to invest effort or attention in subsequent tasks. This reduction in resources was termed "ego depletion."

In the follow-up studies, Gailliot and Baumeister (2007) proposed that effort, as an energy-intensive cognitive process, depends significantly on glucose: "[…] an expensive process in terms of complex brain activity, is especially dependent on glucose" (p. 322). This led to the hypothesis that a drop in blood glucose could explain the ego-depletion effect. Although initially popular, this model failed to be consistently replicated. A first meta-analysis by Hagger et al. (2010), based on 83 studies and 198 independent tests, concluded that ego depletion exists, with a moderate effect size (Cohen's d = 0.62). However, later studies by Carter et al. (2015) and Dang et al. (2016) found no depletion effect after correcting for publication bias. Additionally, Vadillo et al. (2016) conducted a meta-analysis showing that the impact of glucose on self-control-related behavior is unreliable. While debate continues (Inzlicht and Friese, 2019; Baumeister et al. 2024), the glucose depletion hypothesis appears unlikely, particularly considering that total brain energy consumption remains remarkably constant whether one is engaged in an effortful task or not (Raichle and Gusnard, 2002).

Other potential sources of limited resources have been proposed. Wiehler et al. (2022) suggested that glutamate accumulation in the prefrontal cortex might contribute to reduced top-down processing and impulse inhibition. Holroyd and Verguts (2021) speculated that depletion of neurotransmitters like dopamine or the accumulation of toxic waste products of cellular metabolism such as amyloid beta could act as limiting factors. Another possibility is the brain's limited capacity to tolerate lactate buildup, which occurs locally through aerobic glycolysis during task-based activation (Dienel, 2019). Just as excessive lactate in muscles leads to physical fatigue, excessive lactate in the brain after intense mental effort may result in cognitive fatigue, ultimately reducing effort (Raichle & Mintun, 2006; Clairis & Pessiglione, 2024).

Nevertheless, these elements of explanation remain speculative and inconclusive while brain metabolism is a growing area of research. If metabolic resources are not the limiting factor, what else could explain the depletion effect?

One alternative is to view it as a motivational phenomenon. Boksem and Tops (2008) argued that "people will no longer be motivated to perform tasks when energetic costs are perceived to outweigh predicted rewards." Similarly, Inzlicht et al. (2014) framed the depletion effect as a shift in priorities, from extrinsically rewarding labour to intrinsically rewarding leisure: "We suggest that apparent regulatory failures reflect the motivated switching of task priorities as people strive to strike an optimal balance between engaging cognitive labour to pursue 'have-to' goals versus preferring cognitive leisure in the pursuit of 'want-to' goals." Supporting this perspective, Clarkson et al. (2010) found that increasing rewards mitigated the depletion effect, suggesting that performance declines may ultimately be the consequence of some cost-benefit analysis. Hagger and Chatzisarantis (2012) proposed that glucose's role in Baumeister et al.'s experiment may not have been due to replenishing resources but rather to the signalling effects of its sweet taste: even rinsing the mouth with sugar was found to reduce the depletion effect. This means that simply the sweetness of the chocolate, and not glucose in itself, acted as a rewarding signal in the experiment of Baumeister et al. (1998).

This aspect that will be discussed in the next section.

1-4 Valence framework

In a similar vein, Kurzban et al. (2013) provide an alternative explanation to the ego-depletion model, arguing that performing effortful tasks creates an aversive and unpleasant experience. This aversive sensation signals the opportunity cost of effort. More specifically, they suggest that certain cognitive processes can be allocated to different tasks, but not simultaneously. The longer we persist with a particular task, the more aversive it becomes. This aversiveness serves as a signal, indicating that switching to another task—one that utilizes the same cognitive processes—may be more rewarding. In other words, they describe aversiveness as an adaptive feeling that

helps prioritize tasks in a way that maximizes engagement with more rewarding activities (Kurzban et al., 2013, p. 664). As effort, and thus aversiveness, increases, people tend to switch task. Thus, effort has negative valence, and the phenomenology of effort can be understood as the felt output of cost-benefit computations (p. 662).

Opportunity cost signals not only the trade-off between different tasks but also the selection of cognitive strategies used to solve a given task: Kool and Botvinick (2018) argue that when multiple strategies are available for performing a task, individuals choose the one that provides the highest reward relative to its effort cost. To test this idea experimentally, Kool et al. (2010) designed a demand selection task in which participants had to choose between two decks of cards. Each card displayed a number in a specific colour, and, depending on the colour, participants had to perform different cognitive tasks. Unbeknownst to them, while both decks contained cards of both colours, one deck tended to present longer sequences of the same colour, thereby requiring fewer task switches and reducing cognitive demand if chosen consistently. The results confirmed the hypothesis: over time, participants increasingly selected the less demanding task. Importantly, this preference was not driven by minimizing errors or time spent on the task. Moreover, because participants could freely decide which task they wanted to do, demand characteristics were reduced the preference for the less demanding task was therefore attributed to effort avoidance. This feature has allowed many research groups to investigate effort avoidance across a wide range of control demands. The assumption is that participants reveal “a bias” in favour of the less demanding task, revealing avoidance of cognitive demand. It has to be noted, however, that subjects in this experiment were compensated with course credits or nominal payment for participation independently of the task they did. Engaging in the more demanding task did therefore not bring any visible advantage – exactly as the valence approach would predict. One could thus question whether this is “effort avoidance” or “bias” or simply the expression of a rational choice.

Another method for measuring effort avoidance, called cognitive effort discounting, was introduced by Westbrook et al. (2013). Their study employed a discrete-choice experiment using a staircase titration procedure, where participants were sequentially offered different pairs of rewards and effort levels in an N-back working memory task. Participants made choices until they reached a point of indifference between a lower-effort, lower-reward option and a higher-effort, higher-reward alternative. The difference in reward at this indifference point indicated the subjective value of effort. For example, if someone is indifferent between performing a lower-effort task for €1 and a higher-effort task for €3, their subjective cost of cognitive effort for the higher difficulty level would be €2. This measure varies between individuals, quantifying cognitive effort. Westbrook et al. (2013) found that the subjective value of effort decreases as task difficulty increases—meaning that as cognitive effort increases, individuals tend to discount or devalue the associated rewards. In other words, higher-effort tasks are perceived as less valuable because, as the valence framework suggests, they impose greater costs on the individual (see Figure 2 in Westbrook et al., 2015).

Viewing cognitive effort as costly, or aversive, suggests a general tendency to avoid it. This assumption is frequently justified by Hull's (1943) "law of least effort" (Kool et al., 2010) which states that if there are several actions possible to achieve the same result, then the least effortful one will be chosen. People are therefore often depicted as "cognitive misers" who prefer to minimize effort whenever possible (Westbrook & Braver, 2015). Inzlicht et al (2018, p. 339 for example write that "[b]behaviourally, there are clear signs that organisms often dislike and devalue hard work." (p. 339). The valence approach does not necessarily depict individuals as particularly entrepreneurial and active.

The motivational implications of the valence perspective however suggest that greater rewards encourage individuals to take on higher-effort tasks (Shenhav et al., 2021). That is, people are cognitive misers unless they get a greater reward for exerting more effort. This assumption can be tested notably in experimental setups that promises

greater rewards in monetary terms for greater effort. However, there may be a number of rewards that people expect from doing a particular task. The question is how to find out about them without falling into a tautological trap, that is, any choice can be said to be the outcome of some benefit.

This criticism has also been applied to economic analysis. Since Gary Becker's application of economic analysis to various non-market behaviours (Becker, 1976; Teixeira, 2014), cost-benefit models have become a dominant framework for decision-making. However, this approach has drawn criticism, notably from Amartya Sen (1977), who argues that applying economic reasoning universally—treating all behaviours as reducible to a single preference ordering of which the best element is chosen given constraints —creates a "rational fool." More pointedly, Sen writes, "[t]he purely economic man is indeed close to being a social moron" (Sen, 1977, p. 336). Sen's view in particular is that individuals may have a number of reasons why they choose one alternative over another, and a cost-benefit analysis is just one of them. People are social and ethical beings, which influences their decisions. Interpreting the law of least effort as meaning that costly activities must be avoided apart from when they bring some reward, and that individuals always strive to the least effortful activities to achieve a particular goal may align with this critique (see also Job et al., 2024).

A common assumption in economics is that increased effort leads to better performance (e.g., Mas-Colell et al., 1995, Chapter 14). However, the relationship between effort and performance is likely more complex and dynamic, implying that individuals must adapt to context based on their experience of the effects of their effort, and thereby its subjective value (Otto et al., 2021, 2022). The effectiveness of effort in improving performance depends on personal skills, but also on cognitive strategies and approaches to solving tasks. A more effective strategy can lead to better results with the same or even less effort. If an individual has access to a superior strategy, the task may feel less effortful. From the valence perspective, this suggests that identifying an optimal strategy reduces the perceived cost of a task by making it less aversive.

Searching for better strategies can also be costly for the individual, however (Shenhav et al., 2017). A well-designed reward structure or incentive system may encourage individuals to seek out more efficient, less effortful strategies that enhance performance. Simply increasing effort by working more intensively does not necessarily improve performance; instead, it may lead to cognitive fatigue and ultimately reduce performance. This suggests that we cannot answer the question of why effort is exerted independently of knowing how effort is being exerted.

Support for the valence framework has been sought in studies of brain systems involved in valuation and decision making. Some authors have put forward that the cost of effort is associated with activity in the same regions as those engaged by anticipated reward, in particular the ventral striatum, ventromedial prefrontal cortex and orbitofrontal cortex (e.g. Botvinick et al., 2009; Day et al., 2019; Sayli and Badre, 2019). Yet, others argue that the cost of effort is evaluated through a separate system than the reward system including areas from the salience network like the anterior cingulate cortex and the anterior insula (Rudebeck et al., 2006; Prevost et al., 2010; Scholl et al.,2017; da Silva Castanheira et al., 2022; Shenhav et al., 2017). In addition, activity in regions involved in executive control, that is in executing the chosen cognitive activity, like the dorsolateral prefrontal cortex, play also a role in modulating the subjective evaluation of exerted effort (Kool et al 2010; Shenhav et al 2017; Westbrook et al 2019; Sayali and Badre, 2019; McGuire and Botvinick, 2010).

Studies in non-human primates provide valuable information to integrate these different views. Varazzani et al., (2015) and Bornert and Bouret, (2021) tested which neurotransmission pathways are involved in a) the decision to exert cognitive effort (why we engage in effort) and b) during the act of exerting cognitive effort (what happens during effort) respectively. One conclusion of their study is that prior information about a reward, but not the difficulty level, modulates activity of dopaminergic neurons of substantia nigra in relation to the subsequent decision to engage in an effort. This brain region is known to be involved in reward evaluation and

anticipation. In contrast, noradrenergic neurons in locus coeruleus were active after the go signal and this activity explained the variation in the observed behaviour, that is, in exerting effort, and correlated positively with difficulty level, but not with reward magnitude. These neurons are part of the ascending arousal pathway, which controls the individual's general level of arousal. This finding is in line with pharmacological and [18F] DOPA positron emission tomography studies of the cognitive effort discounting paradigm that indicate that dopamine is involved in amplifying the impact of attention on rewards in the cost-benefit computation presiding the decision to engage in an effortful task (Westbrook et al 2020). This could explain inter and intra-individual and differences in the willingness to engage in effort due to variation in dopamine levels.

1-5 Discussion

Both perspectives, the arousal-perspective of effort and the valence-perspective of effort have their advantages and disadvantages. In the preceding sections, we have presented some key characteristics of those two perspectives. Table 1 below summarises these key elements.

One of the key distinguishing factors is the underlying research question, which determines the primary methodological perspective. The arousal framework seeks to understand what happens "in the individual" when they engage in cognitively effortful activities. It measures effort as arousal mostly in objective terms by examining physiological parameters during task performance. The decision to engage in more or less effortful tasks will depend on the different subjective plans and intentions of the individual. The arousal perspective is therefore explicitly vague on the reasons people may have to execute effortful tasks. The valence framework, on the other hand, considers effort to be a subjective experience and studies it specifically from the perspective of "why" an individual engages in cognitively effortful tasks—or why they

Framework	Arousal	Valence
Main question	What happens when effort is exerted?	Why is effort exerted?
Methodology	Second-by-second (continuous, real-time)	Trial-by-trial (discrete, offline evaluation)
Phenomenology of task execution	Low to high arousal Positive or negative feeling	Less to more aversiveness/unpleasantness Negative valence
Measurement	Physiological variables (pupil size, heart rate, skin conductance)	Subjective value Self-reports
Selection of solution strategies:	Minimal arousal; Effective and economical organisation of actions	Minimal cost; Greatest net value
Dominant Associated neural systems	Ascending noradrenergic pathways. Dorsolateral prefrontal regions	Dopaminergic reward pathways. Medial prefrontal regions
How is effort exerted?		
Policy of effort allocation	Subjective plans and current intentions	Cost-benefit computation
Cost of effort	Deficit in performance with more complex and difficult tasks	Aversiveness of exerting effort; Opportunity cost
Effect on performance by exerting greater effort	Null with easier tasks; Drop in performance with raising difficulty of tasks	Not linear Partly dependent on incentive structure
Research field giving prominent focus	Neuroergonomics	Neuroeconomics

Table 1-1 : Summary of the key aspects of the arousal and valence perspective of effort.

choose one activity over another. This is analysed through decision-making (trial-by-trial) experimental designs. The underlying assumption is that engaging in any cognitive task is costly because effort is experienced as aversive. These different foci in the original questions orient not only the experimental designs but also what is measured in terms of neural and physiological correlates. While in the arousal framework markers of selective attention and arousal are sought, often restricting the analyses and interpretations to locus coeruleus norepinephrine dependent mechanisms, in the valence framework markers of expected value are established through computational modelling, with analyses and interpretations often (although not always) restricted to dopamine dependent mechanisms.

Kurzban et al. (2013) suggest that, since our cognitive capacities are limited and cannot be applied to multiple cognitive processes simultaneously, the experience of aversiveness is thus a signal of opportunity cost, indicating that cognitive resources could be allocated to more rewarding tasks. This is an imported concept from economics. However, the original use of opportunity cost in early 20th-century economics was actually a way to sidestep debates about the subjective costs of labour, which were seen as notoriously difficult to quantify (see Adeli Koudehi et al., 2025; Derobert, 2001; Spencer, 2009). Instead, opportunity costs were conceived as an objective proxy for evaluating the cost of forgone labour when leisure was chosen: one hour of leisure costs one hour of sacrificed wages. This provides a tangible and objective measure of forgone benefits. In the current context, however, it is the subjective and directly experienced sensation of aversiveness that are taken to be the opportunity cost—not some forgone benefit. These experienced costs indicate that there may be benefits to reap when switching tasks, but the cost itself lies in the experience, not in the potential lost benefits. If opportunity cost is defined purely as the foregone benefits of another activity, then the experience of aversiveness would have no significance, as costs would be tied solely to what could have been gained elsewhere. This conceptual overlap between cost and opportunity cost raises the question of whether the concept effectively explains what is meant by aversiveness.

Kurzban et al. (2013) illustrate their view with an example: the presence of a smartphone while solving a math problem increases the perceived cost of the math task under the assumption that playing with the smartphone is more desirable (p. 666). This suggests that simply having alternative, more preferred activities available makes an existing task feel more costly, even if nothing changes in the actual execution of the task. Any cognitive effort would thus become very low-cost when fewer preferred alternatives are present—or when those alternatives are themselves highly aversive. Intuitively, however, this does not seem entirely accurate, as already pointed in commentaries of this article (Charney et al., 2013; Bruyneek and Dewitte, 2013).

Westbrook et al. (2013) propose measuring effort in terms of subjective values and apply a discounting paradigm from economics. The extra money needed to complete a high-effort task is taken as a measure of the aversiveness of the additional effort compared to a low-effort task. Yet, what they consider to be the cost of effort is actually not directly observable. Like other representatives of the valence framework, Westbrook et al. (2013) start from the assumption that effort must be costly and that individuals need to be compensated for their effort. But what their experimental design actually tests is not the compensation for some cost, but the willingness to execute a particular task in exchange for some fee. Westbrook et al. (2015, p. 401) themselves note that this discounting framework allows an "accurate quantification of the exchange." It shows that subjects are willing to trade a given level of difficulty in the N-back task for a specific payment. Greater difficulty levels are sold at a higher price than lower ones. That is, we objectively observe is the value at which individuals are willing to engage in a trade, but we do not see the underlying effort, nor the cost to produce that effort. Indeed, we do not even know whether doing an N-back task is costly to individuals at all (other than by assuming it).

The arousal perspective approaches cost differently, as discussed in Section 2. Notably, the word "cost" appears only four times in Kahneman's (1973) book. In this framework, cost is conceptualized as what Kahneman calls "deficit"—the loss in performance due

to excessive arousal or capacity interference. This can be measured objectively through performance declines in dual-task designs. It does not measure the cost of effort in terms of any subjective feeling of aversiveness, but as the consequence on outcome of investing more or less effort, i.e., what individuals are able to do with effort, rather than how they experience it. This perspective also suggests that greater effort does not necessarily lead to better performance.

The emerging field of neuroergonomics addresses similar issues. It builds in large part on the arousal perspective, and studies the neurobiological underpinnings that are responsible for performance deficits and impairments notably in everyday tasks (e.g., Dehais et al., 2020). In contrast to the arousal perspective that relied on the assumption of some limited capacity, the neuroergonomic approach sees performance failures not primarily due to restricted resources, but rather to the prioritization of neural processes. It does also not study explicitly what effort is, but rather the relation between task demand, arousal, mental workload and human performance. For example, an airplane pilot may perfectly well know how to fly a plane but still force a landing after a long flight despite bad weather conditions. The point here would be to study what mechanisms are at work that may lead to impaired decision making, compared to when the pilot evaluates the landing after a shorter flight. Paying a greater reward to the pilot for staying longer in the air may not be the best solution in such a situation. Conceiving of other ways that may help the pilot to reconsider their evaluation of the situation – and thus to change the dominant cognitive mechanism at play – may be another fruitful research avenue to take. Neuroergonomic researchers indeed study neurophysiological states in order to improve workplace design. One aim is to bring individuals into their effort "comfort zone", where they can best solve different tasks. This comfort zone can be conceptualized as an optimal combination of arousal and what is referred to as task engagement, which will depend on people's goals and motivation (see Figure 2 in Dehais et al., 2020). For example, in creating adaptive systems that lower task complexity when high effort is detected, incentive and

motivation could be accounted for in order to further optimize performance and reduce subjective workload (Fairclough, 2009; Schmidt-Hubsch, 2024).

The idea of performance deficits or impairment strongly suggests that in addition to studying changes in the working environment that may affect the prioritization of neurophysiological processes, the question “How is effort exerted?” should also be considered in more detail. This question relates to solution strategies people invent and use during task execution. When solving a task, individuals must first learn how best to approach it. Different people may develop different solution strategies based on prior experience, knowledge, or specific talents. Some may quickly identify highly efficient strategies, while others may not or may take longer. While learning strategies and task execution are key topics in educational psychology, cognitive load theory, and ergonomic studies, many experimental setups in the literature reviewed here do not control for how individuals solve tasks. In other words, these experiments remain agnostic about the exact processes people use to complete tasks. However, accounting for solution strategies is crucial for meaningful comparisons of effort (as measured, for example, by pupil dilation, performance deficits, and self-reports on valence and arousal for example) across different strategies. It can help determine whether the most effective strategies are more or less arousing for different individuals. Within a choice framework, it can also reveal whether individuals prefer more or less arousing strategies and whether trade-offs exist between arousal and strategy effectiveness, particularly if they correlate negatively. That is, would people sacrifice better performance to use a less arousing but also less effective strategy? Will people avoid unpleasant and arousing strategies even though they are efficient, and approach pleasant and less arousing strategies that are less efficient? And how would this change when external incentives are introduced? Are increased rewards for particular tasks changing the solution strategy that people choose? How does this affect other neurophysiological measures?

In this paper, we have shown that in comparison to some decades ago, when much of the research was directed at studying what happens when people engage in effortful tasks, an increased focus of the contemporary literature is on why people engage in effortful tasks and present those reasons, very much in economic terms, as a cost-benefit analysis. While this analysis has the advantage of overcoming the idea of effort as some form of limited resource, it suffers from the unquestioned hypothesis that effort constitutes cost, which people try to minimize, if it would not be for the rewards that may incite them to do some greater effort. The combined questioning of the valence and arousal perspective in the context of finding solution strategies that people would want to choose definitely opens a new set of questions and therefore constitutes an interesting avenue of future research.

Chapter 2

The preceding chapter outlined and defined two distinct theoretical approaches to cognitive effort. The aim of Chapter 2 is to empirically test the predictions derived from these frameworks. To this end, the chapter presents an experimental study specifically designed with the theoretical predictions of both approaches formulated as testable hypotheses. We employed a multimodal methodology that integrates behavioral, introspective, and physiological measures, in order to triangulate the construct of cognitive effort. The chapter concludes with a discussion of the results, evaluating the extent to which the findings support or challenge each theoretical perspective and considering their broader implications for the study of cognitive effort within neuroeconomics.

Cognitive Effort Is Driven by Arousal, Not Valence: Experimental Evidence

Abstract

Cognitive effort can be conceptualized within two broad approaches: the valence approach, which emphasizes more the aversive and costly nature of effort, and the arousal approach, which emphasizes more the association of effort with heightened physiological arousal. This study presents a novel experimental design to adjudicate between the two approaches of cognitive effort. We implemented two tasks commonly used to study cognitive effort, namely the N-back task, a classical working memory task, and the AX-CPT task, a classical sustained attention task. We first taught each participant one of two specific procedures identified to do the task, that is a "cognitive strategy". Then participants engaged in the tasks with varying difficulty levels. For each block of trials, they were informed that they failed to reach a certain performance (20, 40 or 60%) they will have to redo the block. At the end of each two-minute-long block, they reported their perceived effort, arousal, and valence on visual analog scales. We recorded neurophysiological measures, including pupil size and electroencephalographic event-related potentials (P3 and FRN), while participants completed the task and when they received feedback. Behaviourally, we measured "free choice effort" as the extent to which participants continue performing the task even after they had gained enough points to "pass" a block. The findings reveal that reported effort was positively related to reported arousal, pupil dilation and P3. In contrast we observed only a very small positive relationship between effort and reported valence and feed-back related potential. Further the free choice effort was significantly above

zero meaning that participants exerted effort even when it was no longer necessary. These results favour the arousal approach. Lastly, in the N-back task strategy impacted performance and its relation to effort, highlighting the dependence of cognitive effort on cognitive strategy.

2-1 Introduction

Two broad approaches to cognitive effort can be identified in the literature: the valence approach and the arousal approach (chapter 1). The valence approach states that cognitive effort is aversive and costly, and has a negative valence (Kurzban, 2016). It asks why effort is aversive and costly. The answer is that it signals the opportunity cost of engaging in effortful tasks (Kurzban et al., 2013; Westbrook & Braver, 2015; Kool & Botvinick, 2018). If the reward for an effortful task increases relative to that for other tasks, then the task becomes less aversive (although it remains to be shown whether it becomes less effortful). This idea assumes that effort and performance are positively related; greater effort yields better performance and outcomes, and thus higher reward (Shenhav et al., 2021). This approach has mainly been operationalised experimentally in paradigms in which cognitive effort is measured as willingness to earn money through cognitive effort (Westbrook et al., 2013; Shenhav et al., 2013; Westbrook, 2019, 2020; Botvinick et al., 2009).

By contrast, the arousal approach considers physiological markers of autonomic arousal, such as pupil dilation, cardiovascular responses and skin conductance, to be indicators of cognitive effort (van der Wel & Steenbergen, 2018; Fairclough & Houston, 2004; Gendolla et al., 2012; Hess & Ennis, 2011; Naccache et al., 2005; Venables & Fairclough, 2009). Proponents of this approach often ask why cognitive effort is arousing, focusing more on the relationship between the prefrontal cortex and the locus coeruleus (LC) (Sara and Bouret, 2012). While the answer remains speculative, it has been suggested that cognitive effort is arousing due to the brain's limited

capacity. Arousal is thus necessary to inhibit irrelevant tasks and intensify relevant processing, thus intensifying selective attention (Kahneman, 1973). “Mental resources”, which are distributed and stable at baseline, become more unitary and unstable with increased effort allocated solely to the task at hand (Kahneman, p. 149). According to this approach, although the decision to exert effort may be voluntary, the allocation of effort during exertion is involuntary. Cognitive effort supplies only the minimum resources demanded by task difficulty — no more, no less. Consequently, it is predicted that there is no relationship between cognitive effort and performance.

In this paper, we present a novel experimental design to test the predictions of these two approaches. The core concept of the experiment involves participants indicating the level of effort they exerted and the degree of arousal and valence they experienced while performing a mentally demanding task of varying difficulty levels immediately after completing it. To obtain objective measures of arousal, valence, and cognitive effort, we also recorded pupil and brain activity using electroencephalography (EEG).

We recorded pupil size (PS) because, since the work of Hess and Polt (1964), it has been well documented that pupil size correlates positively with arousal and cognitive effort (see Wel and Steenbergen, 2018, for a review). Joshi et al. (2016) famously provided direct electrophysiological evidence linking fluctuations in pupil diameter to spiking activity in the noradrenergic neurons of locus coeruleus (LC) on a moment-to-moment basis. Using simultaneous recordings of LC neuronal activity and pupillometry in awake, head-fixed mice, the study demonstrated that the LC firing rate reliably predicted subsequent pupil dilations with a latency of approximately 300–500 milliseconds. Similar correlations were observed in the superior and inferior colliculi and the anterior cingulate cortex; however, the LC exhibited the most robust and consistent relationship with pupil dynamics. This study showed that the use of pupillometry is a reliable candidate to proxy the dynamics of the arousal state.

We considered the P3 component of the evoked response to target stimuli in a visual cognitive task from the EEG signal, as this component has been shown to reflect phasic

arousal. Nieuwenhuis et al. (2005), in reviewing behavioural and electrophysiological evidence of the P3 origin, argued that it results from the phasic activity of noradrenergic (NA) neurons in the locus coeruleus (LC). LC neuron activity closely correlates with the level of autonomic arousal. These neurons are known to exhibit phasic activity in response to highly salient, unconditioned environmental stimuli, as well as task-relevant stimuli, across various modalities (Aston-Jones & Bloom, 1981; Aston-Jones et al., 1994; Foote, Aston-Jones & Bloom, 1980). According to the 'LC-P3' hypothesis, it is these phasic activities that are responsible for the display of the P3 in scalp EEG recordings. The LC phasic response is driven by the meaning and frequency of attended environmental stimuli rather than their physical characteristics (Nieuwenhuis et al., 2005). The conditions that trigger LC phasic activity are strikingly similar to those that elicit the P3 wave.

The parallel between the P3 response and the LC response is further substantiated by an oddball study in which both LC neuronal activity and scalp electrophysiological potentials were recorded in monkeys (Aston-Jones et al., 1991). In this study, LC activity and scalp potentials from frontal and parietal electrodes, measured 200–300 ms after the stimulus, were selectively enhanced by target stimuli. Additionally, changes in LC activity and scalp potentials occurred concurrently. It is therefore assumed that the P3 component follows the LC phasic response after a fixed period of time. This close temporal relationship lends weight to the idea that the P3 is an electrophysiological manifestation of LC phasic activity, providing additional support for the LC-P3 hypothesis.

We also considered the feedback-related negativity (FRN) to be a measure of cognitive effort based on valence. The FRN is an ERP that appears 200–400 ms after the presentation of performance feedback, and its amplitude is more negative for monetary and non-monetary loss than for gains. Miltner (1997) first observed a negative deflection after the presentation of feedback for incorrect versus correct trials from frontal EEG electrodes. Gehring and Willoughby (2002) demonstrated that this

negative deflection is due to loss versus gain rather than to incorrect versus correct responses. In their gambling task, they were able to dissociate loss and gain from incorrect and correct performance. They observed that the FRN was negatively deflected in the "loss and correct" and "loss and incorrect" blocks relative to the "gain and correct" and "gain and incorrect" blocks.

Holroyd and Coles (2002) proposed that the FRN reflects the functioning of the neural system that underlies reinforcement learning. They argued that the FRN represents a reward prediction error signal originating from dopaminergic projections in the striatum to the anterior cingulate cortex (ACC), which then continues towards motor areas. According to their hypothesis, a decrease in phasic dopamine firing disinhibits ACC neurons, generating a more negative signal. Conversely, an increase in phasic dopamine firing inhibits ACC neurons, resulting in a more positive signal. Subsequent studies have shown that positive "rewarding" feedback — whether monetary, anticipated monetary, performance-related, affectively valanced, socially related, or concerning aversive or non-aversive outcomes — evokes a larger positive peak 200–400 ms after presentation compared to negative feedback, leading to the term "reward positivity" (Nieuwenhuis et al., 2005; Yeung & Sanfey, 2004; Tunison et al., 2009; Rigoni et al., 2009; Flores et al., 2015; Williams et al., 2019; Bauer et al., 2023).

The reason behind why in the current experiment we decided to use FRN as a valence measure of cognitive effort is because Bogdanov et al., (2022) showed a positive correlation between probability of choosing high effort option as compared to low effort option for the participants with higher FRN.

Although several experiments support this interpretation of the FRN, Talmi et al. (2013) cast doubt on it by showing that FRN deflection can be amplified by unpleasant (e.g. electrical shock) and pleasant (e.g. money) stimuli. Put simply, a higher level of punishment than expected also evokes stronger FRN. The authors interpret these results as supporting the salience hypothesis of Alexander and Brown (2011), which states that the signal from the striatum passing through the ACC to the motor areas is

sensitive to discrepancies between expected and unexpected outcomes, regardless of their emotional valence. To investigate this further, Heydari and Holroyd (2016) designed a T-maze task in which subjects wandered freely through the maze, accidentally encountering positive (money) or negative (shock) stimuli. The results showed that the feedback stimuli elicited a typical FRN in both cases, in line with the reinforcement learning hypothesis. However, this signal was more positive in response to stimuli predicting the omission of a possible punishment than to stimuli predicting a forthcoming punishment. This was inconsistent with the salience hypothesis. One difference between the experiments of Talmi et al. (2013) and Heydari and Holroyd (2016) that could explain the discrepancy in results is that participants in the former study had no opportunity to influence the outcome. Which this cases do not concern FRN in study of effort because in the effort experiments because to exert effort means to have an opportunity to influence the outcome.

The final measure of the experiment, “free choice effort” (FCE) is behavioural. “Free choice” is a measure of how much participants exerted effort more than what was required, related to their intrinsic motivation (Deci, 1971; Ryan and Deci, 2000). The assumption for using this measure is that if there is no extrinsic reason to do the effort (e.g. no requirement, no reward and no approval); then the more effort participants exert, the more intrinsically motivated they are. In the context of cognitive effort research, similar operationalizations of FCE have been employed as implicit measures of an individual's willingness to engage in mentally demanding tasks (Baumeister et al., 1998; Hagger & Chatzisarantis, 2005; Lepper et al., 1973). In these paradigms, participants are typically given the opportunity to continue working on a cognitively challenging task—such as solving puzzles or completing logic problems—after “the main task” (e.g. reaching the required score in our experiment, see figure 2-1). The amount of time or number of trials participants freely choose to engage with such tasks is used as a proxy for their intrinsic motivation to exert cognitive effort. The present study adopts this approach to quantify participants’ cognitive effort exertion, thereby offering insight into the aversiveness hypothesis of cognitive effort.

The final note about the indices is that we also examined the "error-related negativity" (ERN) as a component of the response-locked ERP that occurs almost simultaneously with an erroneous response. ERN are considered a neural marker of performance monitoring, reflecting the brain's ability to detect and evaluate errors in real-time (Kirschner et al., 2021). It has been argued that the presence of ERN indicates an individual's awareness of their performance. This measure did not serve a purpose on the main hypotheses of the study, and it only was used as a periphery index of participant's performance monitoring during cognitive effort exertion.

Crucially, we controlled for cognitive strategies used by participants in this experiment, as prior studies have shown that the strategy used to solve a task can influence the perceived level of task difficulty, and thereby cognitive effort (Kahneman and Wright, 1971). To the best of our knowledge no one has yet ever verified the differences in cognitive effort when people perform the same cognitive task but employing a different strategy (or cognitive procedure). Employment of different cognitive strategies can have profound impact on the effortfulness of the task, the performance of the task as some strategy can be more "efficient" (perform better) than the others (Laine et al., 2018) and possibly the pleasantness of the task experience. To gain insight into the generalizability of the results across tasks, we will be employed two widely used tasks in neuroscience with well-known cognitive control strategies and different levels of difficulty: a working memory task (N-back) (Kirchner et al 1958; Ralph, 2014) and a sustained attention task (AX-CPT) (Braver et al., 2016). Participants performed each task in two different sessions on separate days (figure 2-1 a).

The two sets of predictions by the two approaches of effort are summarized in table 2-1: If effort self-reports can be predicted by valence or arousal self-reports and their physiological indices (FRN for the valence and PS and P3 for the arousal), that will speak more in favour of the valence or arousal approach, respectively. In addition, regarding the relationship between cognitive effort and performance within each difficulty level, the arousal approach predicts a constant function, that is no change in

performance as a function of effort, whereas the valence approach predicts a positive correlation. Finally, the aversive hypothesis of cognitive effort by the valence approach predicts FCE to be zero.

It is important to note that except from the predictions about performance, the two approaches are not mutually exclusive and antagonist. That is to say cognitive effort can be both aversive and arousing. For example, the reported effort can have positive correlation with reported arousal and negative correlation with reported valence at the same time and FCE be zero.

Framework	Arousal	Valence
Phenomenology	Positive relation between reported effort and reported arousal	Negative relation between reported effort and reported arousal
Physiology	Positive relation between reported effort and PS P3	Negative relation between reported effort and FRN
Performance	No relation between reported effort with score	Positive relation of reported effort with score
Free choice effort	No prediction	Zero

Table 2-1: The table is the summary of the predictions coming from the two approaches. With respect to the **phenomenology** of cognitive effort, based on the arousal approach we expect to see a positive correlation between reported effort and reported arousal and based on the valence approach we expect to see negative correlation between reported effort and reported valence. With respect to the **physiology** of cognitive effort, based on the arousal approach we expect to see positive correlation between reported effort and pupil size (PS) and P3 component analysed from the EEG. And based on the valence approach we expect to see positive correlation between reported effort and feedback-related negativity (FRN) component analysed from the EEG. With respect to the **performance** of cognitive effort, based on the arousal approach we expect to see no relationship between reported effort and score within difficulty levels, whereas the valence approach predicts positive correlation between reported effort and score within difficulty levels. Lastly, based on the valence approach we expect free choice effort to be zero.

2-2 Methods and Materials

2-2-1 Participants

Thirty young adult participants (19 females, 11 males; mean age = 24 years, SD = 2.8; age range = 20–29) were recruited from the Aix-Marseille University community. All participants were right-handed, had normal or corrected-to-normal vision (participants did not wear glasses during testing), and reported no history of neurological or psychiatric disorders, drug abuse, or current use of psychotropic medication. Prior to each session, participants were instructed to abstain from alcohol and drug use for at least 24 hours and were asked to report their food and beverage intake on the day of testing.

Participants had average working memory capacity as assessed by the Digit Span subtest of the Wechsler Adult Intelligence Scale–Fourth Edition (WAIS-IV), which includes Digit Span Forward, Backward, and Sequencing components. This subtest evaluates short-term memory, attention, and working memory manipulation. The average total raw score was 31 (SD = 4.9), corresponding to standard scores between 9 and 14 based on WAIS-IV normative data.

Participants were tested in two sessions, scheduled one week apart, with each session devoted to a distinct, experiment-specific cognitive task, either a modified AX-CPT or a modified N-back task (see Task Description for details). Sessions were conducted either at 10:00 AM or 2:00 PM, independent of task type or group assignment, to minimize potential circadian confounds. Task order was counterbalanced across participants: approximately half completed the AX-CPT task first, while the remaining half began with the N-back task. Participants received €30 per session by attendance, totalling €60, irrespective of task performance or completion.

Participants were randomly assigned to one of two groups (n = 15 per group), with each group trained in a different cognitive strategy (see Task Description). Group assignment and task-strategy sequences were determined using an alternating assignment procedure. Two participants (one in each group) were excluded from the analysis due to an inability to complete one of the tasks: both struggled to meet performance thresholds after multiple attempts and voluntarily withdrew, citing task difficulty and cognitive overload. These sessions were terminated at their request.

All sessions were administered by the same experimenter, who was not blind to group assignment due to methodological constraints associated with strategy instruction (see Task Description). The study was approved by the research ethics board “Comité de protection des personnes Ile de France II” (reference number: 23.03885.000258). All participants provided written informed consent prior to participation.

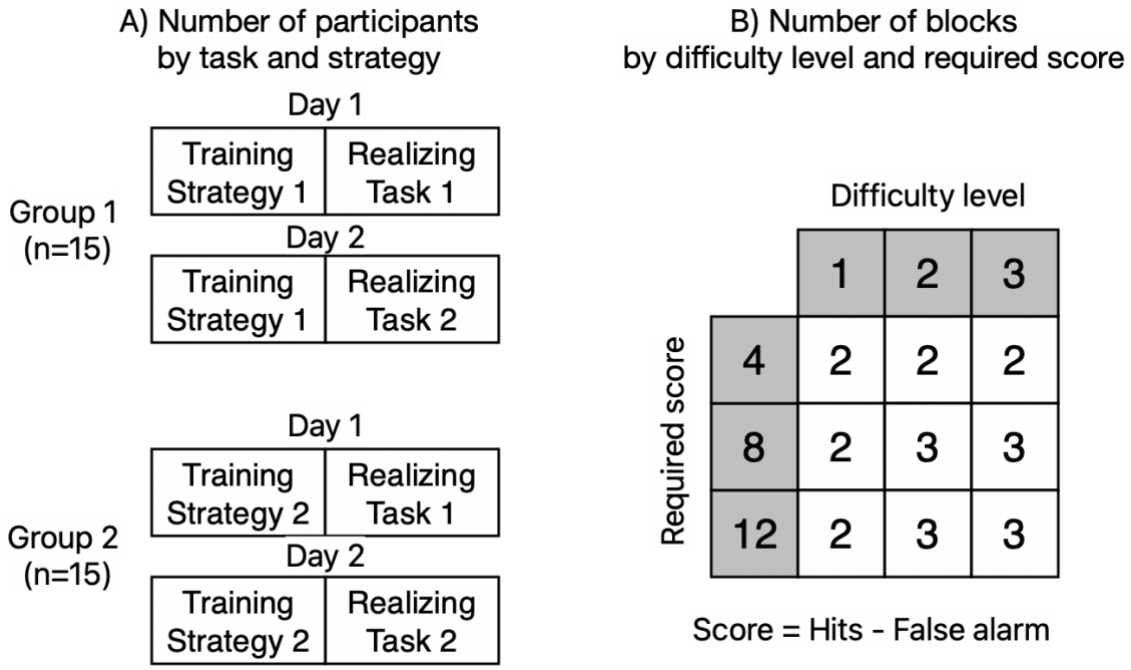

Figure 2-1: Panel A) Study design. The participants are divided into two groups. Each group trains for a specific strategy for each task. The two tasks are performed on different days. Each session (each day) consists of a training and a testing part. Panel B) Number of blocks performed for each combination of difficulty level and required score (e.g. there are 2 blocks that had required score 4 and difficulty level 1). Score is defined as number of hits (correct click) minus number of false alarms (wrong click), and it wasn't allowed to be negative. The participants are instructed that if they fail to reach the required score, they have to repeat the block up to three times if necessary.

2-2-2 Sample Size

Based on prior EEG literature of event-related potentials in N-back tasks (e.g. Pesonen et al., 2007; Brouwer et al., 2014) and AX-CPT task (Braver et al., 2001; Chatham et al., 2009; Gonthier et al., 2016), we anticipated a medium effect size and adopted Cohen's d = 0.6 for the contrast between the least vs most effortful difficulty level of

these tasks with EEG (as EEG's effect size is lower than Pupil with Cohen's d = 1.17 (Pan et al., 2024)). Before the experiment we assumed $\alpha = 0.05$ (two-tailed) and power $(1 - \beta) = 0.90$. The power analysis (paired-samples t-test) indicated that a minimum of 26 participants to detect an effect of this size with sufficient statistical power.

2-2-3 Procedure

Participants were tested over two sessions, each devoted to a different tasks on separate days. Upon arrival for each session, participants were escorted to the experimental suite and seated comfortably in an armchair while the EEG cap and eye-tracker were fitted.

Each session began with a structured training phase. This served not only to ensure task understanding and minimize on-line learning effects, but crucially to standardize participants' approach to the task (hereafter referred to as their "cognitive strategy"). By prescribing and verifying a specific strategy up front, we maintained tight experimental control over how the task was performed, which is essential when interpreting both subjective effort ratings and neurophysiological markers of cognitive effort.

The training phase began with participants reading the general task instructions, followed by the detailed cognitive-strategy guidelines for their assigned task (appendix page 222). They were then presented with examples of 1-back (12 trials), 2-back (12 trials), and 3-back (24 trials) on paper, identical for both strategy groups and asked to write a brief, step-by-step summary of how they would implement the strategy on each trial (appendix page 239). The experimenter intervened only when participants requested clarification or had difficulty understanding the examples or articulating their strategy.

Once comprehension was confirmed, participants proceeded to computer-based training. They completed at least four blocks of 60 pseudo-randomized trials each, with each block lasting 2 minutes. Throughout these trials, participants verbalized every cognitive step of the strategy (think-aloud), allowing the experimenter to monitor adherence in real time using a standardized checklist and scripted prompts (appendix page 245). No trial-by-trial feedback on accuracy or reaction time was provided; participants only saw their overall score at the end of each block. The experimenter offered minimal verbal encouragement or strategy reminders if necessary but otherwise remained silent to avoid influencing the learning process. Mastery criteria differed by task. In the N-back task, training continued until participants achieved a minimum 3-back score of 4, with a maximum of eight blocks allowed (no participant exceeded eight blocks). In the AX-CPT task, all participants completed exactly four blocks of training. Participants could request brief breaks between blocks. Breaks were granted with a minimum duration of 8 seconds.

Upon completion of training, participants entered the test phase, during which they performed the task silently and without experimenter feedback. This phase comprised 22 blocks of 60 trials each (2 s per trial). Every block was defined by one of three difficulty levels and paired with one of three minimum-score thresholds (Figure 2-1b). Difficulty and score requirements were pseudo-randomly interleaved in a fixed sequence—identical for all participants—to maintain maximal experimental control. At the start of each block, an on-screen header displayed its difficulty level and required minimum score. Score was computed as the difference between the number of hits and the number of false alarms. However, if negative (the number of false alarm more than hits, it was adjusted to zero. The choice about the definition of score was because to punish participants (by losing score) they just “guess” the target and to avoid random clicking. It is also an intuitive reflection of performance for the participants as it solely depends on their clicks. They were instructed that if they did not reach the required score, they will have to redo the block. Block repetition was allowed up to three times, after which the experiment would proceed to the next block even if the required score

was not reached. (This definition of score also has nearly perfect correlation with d-prime ranging from 0 to 4; see Appendix).

Participants did not see ongoing performance metrics during a block, so as not to distract from their prescribed cognitive strategy. Instead, after each block (and any necessary repeats), they completed three horizontal visual analogue scale (VAS) ratings (Figure 2-2) with anchors labelled "min" and "max," for cognitive effort, "passive" and "active" for arousal, "negative" and "positive" for valence with no time limit. On appearance the cursor was hidden, and it appeared after participants' click using a trackball mouse.

1. Cognitive effort: "Your level of cognitive effort is:"
2. Arousal: "How active / passive do you feel right now?"
3. Valence: "How positive / negative do you feel right now?"

The wording and the semantic structure of the arousal and valence items were based on Sosnowska et al. (2017).

Immediately following the VAS, participants saw a brief numeric feedback screen: "you collected [score] points". Feedback was withheld until after the VAS to avoid metacognitive biases: pilot data showed that immediate performance feedback—even within a single difficulty level—systematically altered effort ratings.

If participants failed to meet the required score, they repeated the same block up to three times, with a minimum 8-second rest between repetitions. After three unsuccessful attempts, they advanced to the next block regardless of performance. Finally, at the end of each session, the experimenter conducted a semi-structured debriefing interview (Appendix page 241) to probe participants' experiences and strategy adherence. The contribution of the required score manipulation is three-fold: (1) it increases effort variability within each difficulty level; (2) it discretizes success

versus failure at the block level; and (3) it incentivizes sufficient effort while avoiding endless repetition.

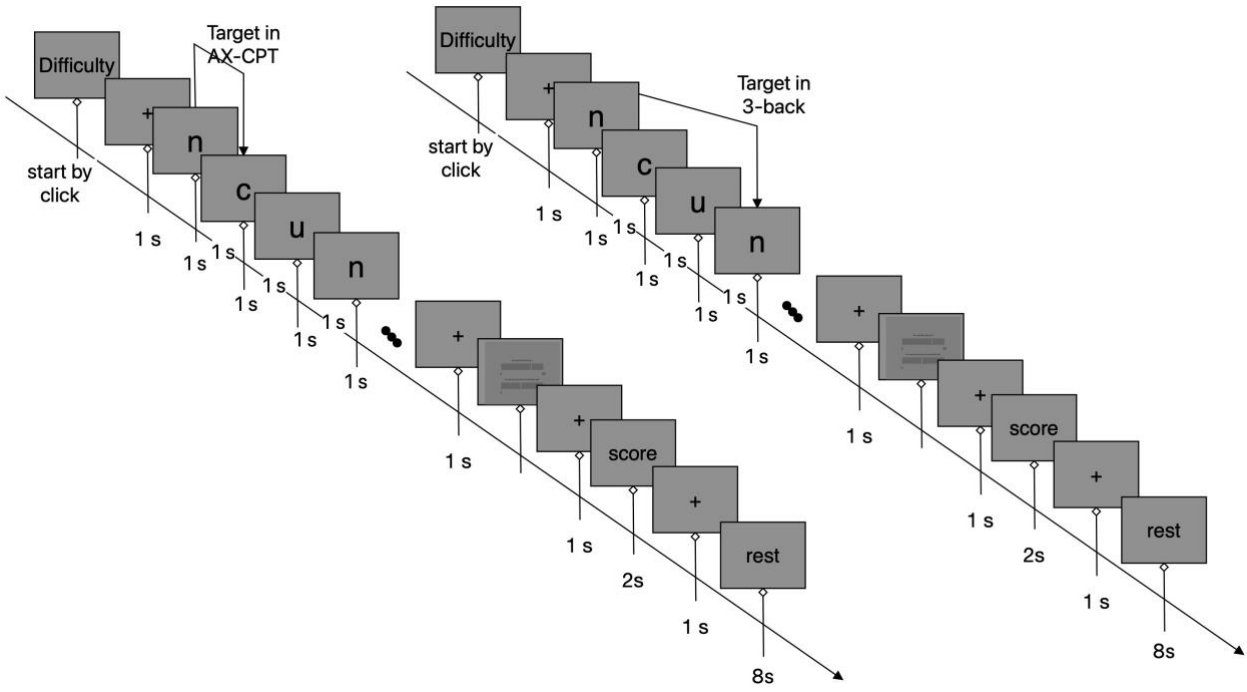

Figure 2-2 : Timeline of a block for both tasks and for both training and test phases. In the first slide, the difficulty level as shown, and with the participants pressing a button, the sequence of trials began. Each trial consisted of 1 second letter presentation followed by 1 second inter-stimuli interval. At the end of the 60 trials, three visual analogue scales were presented on which participants had to evaluate: how effortful the block was for them, how active/passive they felt, how positive/negative they felt. Afterwards their score was displayed. Finally, they will rest for at least 8 seconds. The next block started by the mouse click from the participant.

2-2-4 Task Description and Cognitive Strategies

2-2-4-1 N-back task

Task

We implemented a continuous N-back task (Kirchner, 1958) using a stream of lowercase letters (n, u, m, c, s). These letters were selected for their consistent visual curvature and similar auditory duration when voiced, thereby minimizing perceptual confounds across trials. Each letter was presented centrally on the screen for 1 s (size of stimuli), followed by a 1 s inter-stimulus interval (ISI), resulting in a fixed trial duration of 2 s. Participants were instructed to click the left mouse button whenever the currently displayed letter matched the letter shown N trials earlier, where N was set to 1, 2, or 3 depending on block difficulty. No response was required for non-matches, and the absence of a click was interpreted as the participant judging the item to be a non-target. No explicit "no" button was provided, and no feedback was delivered during trials.

Each block consisted of 60 trials, comprising 20 targets (33%) and up to six lure trials (≤ 10%). Lures were non-targets that involved letter repetitions at incorrect lags (e.g., in a 3-back condition, the sequence n–c–c–n contains a lag-1 repetition "c–c" that may lure the participant into a false positive response). Targets and lures were evenly distributed throughout each block and were pseudo-randomized to avoid consecutive occurrences of either. Reaction times were recorded only for trials on which participants responded (i.e., hits or false alarms); no reaction time data were available for correct rejections or misses.

Each block was paired with one of three score thresholds (4, 8, or 12), defined as number of hits minus number of false alarms. Difficulty level (i.e., N = 1, 2, or 3) and

required score were pseudo-randomly interleaved across blocks in a fixed sequence shared by all participants (see Fig. 1b). Blocks with the lowest threshold (score = 4) were underrepresented to emphasize blocks with higher cognitive demand.

Cognitive strategies

To solve the N-back task, participants were trained to use one of two cognitively distinct working memory strategies: the Rolling and Static strategies (Ralph, 2014). Both involve the continuous updating of letter sequences but differ fundamentally in how the memory rehearsal is maintained and assessed for target's detection (see Figure 2-3 for visual illustration).

In the Rolling strategy, participants maintain a moving window of N+1 consecutive letters in working memory (e.g., in a 3-back task: n–u–c–s). For each new trial, they compare the first and last letters in this buffer (e.g., is n == s?). Regardless of the outcome, the buffer is then "rolled forward" by one position: the first letter is dropped, and the new letter is appended to the end (e.g., if the new letter is u, the buffer becomes u–c–s–u). A match between the first and last elements prompts a response.

In contrast, the Static strategy involves maintaining a fixed N-item buffer (e.g., n–u–c in a 3-back task) that is updated only as needed. With each new trial, participants compare the incoming N-length subsequence to the one currently held in memory. If the new sequence differs, they update the buffer accordingly (e.g., s–u–c, then s–n–c, then s–n–u). A target is detected when the current stimulus sequence exactly matches the buffer's content, signalling that no update is required. For example, in the sequence n–u–c–s–u, the buffer transitions from n–u–c to s–u–c, and then remains s–u–c; this repetition triggers a response.

2-2-4-2 AX-CPT task

Task

We employed a letter-based AX continuous performance task (AX-CPT) adapted from established protocols (Cohen et al., 1998; Gonthier et al., 2016; Paxton et al., 2016). Stimuli consisted of a continuous stream of centrally presented lowercase letters (n, u, m, c), identical to those used in the N-back task. Each letter appeared for 1 s, followed by a 1 s inter-stimulus interval (ISI), yielding a fixed 2 s trial duration.

Participants were instructed to click the left mouse button when the letter c appeared immediately after the letter n (i.e., an n–c target pair). No response was required for all other letter combinations. “Target” responses (hits) and “non-target” decisions (correct rejections) were operationalized as left clicks and withheld clicks, respectively. The response window was strictly limited to the 1 s display duration of each stimulus. No feedback was given during the trials.

Task difficulty was manipulated by adjusting the contingency between the contextual cue (n) and the probe (c) relative to non-target pairs, notably m–c. Three levels of contextual difficulty were defined by varying the proportion of n–u (AY), m–c (BX), and m–u (BY) sequences while keeping the number of n–c target pairs fixed at 20 per block:

1. Low difficulty: 20 × n–c, 0 × n–u, 5 × m–c, 5 × m–u
2. Medium difficulty: 20 × n–c, 2 × n–u, 3 × m–c, 5 × m–u
3. High difficulty: 20 × n–c, 5 × n–u, 0 × m–c, 5 × m–u

Each block comprised 60 trials and was paired with one of three minimum score thresholds (4, 8, or 12), defined as the number of hits minus number of false alarms. Block-level difficulty and required score were pseudo-randomly assigned in a fixed order across participants (see Fig. 1b), following the same design structure as the N-

back task. Fewer blocks featured the lowest threshold (score = 4) to emphasize more demanding control requirements.

Cognitive Strategies

Performance on the AX-CPT was hypothesized to rely on one of two cognitive control strategies: proactive or reactive control (Braver, 2012). These strategies differ in the timing and focus of attentional and mnemonic engagement during the task.

p(n|c)	100%	90%	80%
nc	20	20	20
nu	0	2	5
mc	5	3	0
mu	5	5	5
q(c|n)	80%	90%	100%

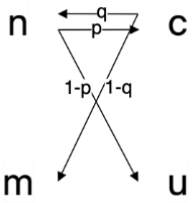

Table 2-2: Contingency structure of AX-CPT blocks across difficulty levels. Each column corresponds to a distinct level of contextual cue–probe correlation, operationalized via the conditional probability p(n|c)—the likelihood that a "c" was preceded by an "n"—and its inverse q(c|n)—the likelihood that an "n" is followed by a "c." These probabilities were manipulated by varying the number of n–u, m–c, and m–u filler sequences while holding the number of n–c target pairs constant at 20 per block. As p(n|c) decreases (from 100% to 80%), "c" becomes a less reliable signal of preceding context, making the task more challenging for reactive control. Conversely, higher q(c|n) values enhance the predictive validity of the context cue "n," facilitating proactive strategy use. The diagram (right) illustrates the probabilistic dependencies between stimuli.

In the proactive strategy, participants actively maintain the contextual cue (i.e., the letter "n") in working memory in anticipation of the upcoming probe. This strategy involves sustained attention to context and enables rapid responses if the expected target ("c") follows. In this mode, participants become "alert" when an "n" is encountered and prepare a response contingent on observing "c" on the subsequent trial.

In contrast, the reactive strategy defers control engagement until the appearance of the probe stimulus. Here, participants become alert upon seeing the letter “c” and then retrieve the identity of the preceding item to determine whether it was an “n.” This approach relies on retrospective memory rather than sustained maintenance of context, and is more vulnerable to interference from non-target sequences such as m–c or n–u.

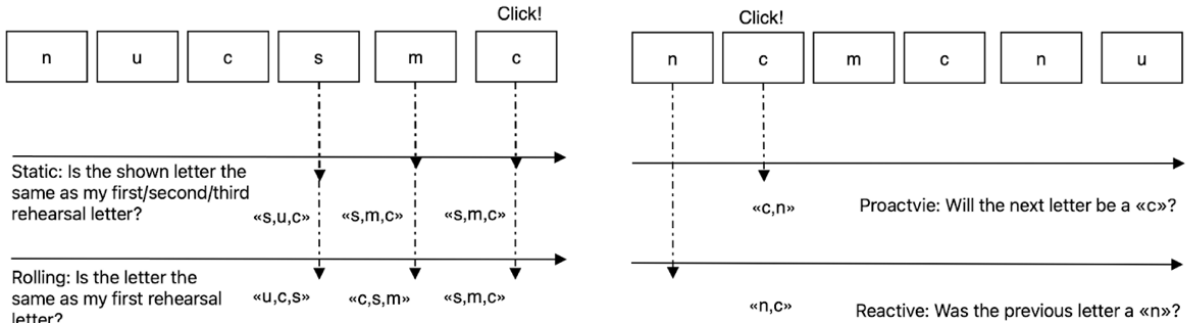

Figure 2-3: The figure describes the strategies of the two tasks. Left hand side is the N-back task. The series of letters in each trial are presented on the monitor indicated by the boxes are n, u, c, s, m, c. In the static strategy the participant rehearses the letters in her mind successively as: “n”, “n-u”, “n-u-c”, “s-u-c”, “s-m-c”, “s-m-c”. When she encounters two successive identical triplets, like in the last two repetitions of our example, she knows that she should click. In the rolling strategy the participant rehearses in her mind n, n-u, n-u-c, u-c-s, c-s-m, s-m-c. Because the first letter c in c-s-m is updated by the same last letter c in s-m-c the participant knows that she should click. Right hand side is the AX-CPT task. The series of letters that are presented in each trial are: n, c, m, c, n, u. In the proactive strategy the participant is alert on the letter n and look forward to seeing letter c. On contrary, in the reactive strategy the participant is alert on the letter c and look backward to remember letter n.

The relative effectiveness of each strategy depends on the degree of cue–probe contingency. As shown in Table 2-2, block-wise difficulty was manipulated by systematically varying the predictive validity of “n” for “c” (proactive-relevant) and of “c” for “n” (reactive-relevant). When the probability of “c” following “n” is high (e.g., 100%), the proactive strategy is more efficient, as the contextual cue reliably forecasts the target. However, as this contingency weakens (e.g., 80%), and non-target m–c sequences become more frequent, the reactive strategy becomes less effective,

increasing susceptibility to false alarms. Thus, task demands differentially favour one strategy over the other across difficulty levels (see also Fig. 2-3 for a schematic illustration).

2-2-5 Data recording

2-2-5-1 EEG

EEG was recorded continuously with an Active-Two Biosemi system, using 64 channels (with five external electrodes, two on mastoids, two on temples, and one below the left eye) with a sample rate of 512 Hz. The electrodes' offset values were checked prior to recording and kept under 25mV. The system was synchronized to the stimulation computer through a parallel port. Yet to ensure precise timing between the triggers and stimuli displayed on the monitor, two photocell sensors, placed on the extreme right and left sides of the monitor, masked from the subject vision, were flashed simultaneously to each letter stimulus. These signals can then be used offline to check correct synchronization between visual display and EEG trigger and eventually adjust.

2-2-5-2 Eye Tracker

We used an Eyelink 1000 plus desktop-mount infrared-video based eye tracker to record the eye position and pupil diameter from the right eye, with a sampling rate of 500Hz. Head movement was restrained by having participants place their head on a chin and forehead support. A nine-point calibration was carried out at the beginning of the session and repeated when participants took longer breaks or in case of drift.

2-2-5-3 Stimulus

The experiment was implemented in PsychoPy (Peirce, 2019) for stimuli and visual analogue scale presentation, the recording of clicks responses on a trackball, and their time (RT). Stimuli were presented in black on an isoluminant grey background on a 27-inch Acer XB273 monitor with 1920 x 1080 resolution (viewing distance: 80 cm). Two photodiodes were affixed to the central left and right edges of the screen to capture stimulus onset and synchronize trigger timing. Testing took place in a dimly lit room contained within a Faraday cage to minimize acoustic and electromagnetic interference.

2-3 Data analysis

2-3-1 Behavioural data

All behavioural analyses were performed in R using the « lme4 » (Bates et al. 2014); "emmeans" (Lenth, 2025) and "lmerTest" (Kuznetsova, Brockhoff, and Christensen 2017) packages. For all linear mixed-effects models, fixed effects were estimated via maximum likelihood and statistical significance assessed with Satterthwaite-corrected degrees of freedom (via lmerTest). Participant was included as a random intercept in every model to account for individual differences.

2-3-1-1 Response time

Reaction times (RTs) were analysed on trials where participants clicked; namely, hits (correct target detections) and false alarms (incorrect responses on non-targets). By design, no response was recorded for correct rejections or misses, and responses were limited to the 1 s stimulus presentation window (total trial duration = 2 s). Also, the

outliers were identified as reaction times beyond 3 standard deviation from the mean, were removed.

We first computed the averaged RT across all hits in a block. We modelled averaged RT as a function of subjective effort, cognitive strategy, difficulty, and practice (block number) using a linear mixed-effects framework we tested the relationship between response time and reported effort. Specifically, for block i of participant j:

$$RT_{ij} = \beta_0 + \beta_1 E_{ij} + \beta_2 S_j + \beta_3 E_{ij} \times S_j + \beta_4 D_{ij} + \beta_5 B_{ij} + U_{sub[j]} + \epsilon_{ij} \qquad 2\text{-}1$$

where RT_{ij} is the average response time of block i of participant j; E_{ij} is the self-reported effort rating; S_j is the between-subject factor (Static vs. Rolling or Proactive vs. Reactive); D_{ij} is the block's task difficulty level (N-back: N = 1,2,3; AX-CPT: high / medium/ low contingency); B_{ij} is the block number (e.g., 1–22); $U_{sub[j]}$ is the random intercept for participant j to address individual heterogeneity; and ϵ_{ij} is residual error.

2-3-1-2 Performance

Block-level performance was indexed by Score, defined as the number of hits minus false alarms (range: 0–20 per block). To examine the relationship between subjective effort and performance, we first analysed the data separately for each combination of cognitive strategy (Static vs. Rolling for the N-back; Proactive vs. Reactive for the AX-CPT) and task difficulty (three levels), resulting in six subsets. To assess how subjective effort predicted Score within each combination of Strategy and Difficulty (2 x 3 subsets in total), we fitted the following linear mixed-effects models:

$$P_{ij} = \beta_0 + \beta_1 E_{ij} + \beta_2 B_{ij} + U_{sub[j]} + \epsilon_{ij} \quad \text{2-2}$$

Where P_{ij} is score for participant j and block i: E_{ij} is the self-reported effort rating for block i, B_{ij} is the block number (1–22 or more depending on the number of repetition), controlling for learning or fatigue, $U_{sub[j]}$ is the participant-specific random intercept and ϵ_{ij} is residual error.

Visual inspection of Q–Q plots confirmed that, within difficulty level, Score was approximately normally distributed. Accordingly, we used a Gaussian link function for all models.

To assess the broader impact of cognitive strategy on performance across all difficulty levels, we extended the model to include Strategy as a between-subject fixed effect, along with its interaction with Effort, and included Difficulty as a block-wise covariate:

$$P_{ij} = \beta_0 + \beta_1 E_{ij} + \beta_2 S_j + \beta_3 E_{ij} \times S_j + \beta_4 D_{ij} + \beta_5 B_{ij} + U_{sub[j]} + \epsilon_{ij} \quad \text{2-3}$$

2-3-1-3 Relations between the visual analogue scales

Ratings of cognitive effort, arousal, and valence (collected via visual analogue scales) are known to be sensitive to prior performance and time-on-task (Hockey, 2013). To examine the intrinsic relationships among these subjective states, we first removed variance associated with score (Performance on the current, P_{ij}, and preceding block, $P_{i-1\ j}$) and Block number B_{ij} (a proxy for habituation or fatigue).

For each participant and task, we independently modelled each rating (Valence V_{ij}, Arousal A_{ij}, Effort E_{ij}) as a function of these covariates:

$$V_{ij} = \beta_{11}B_{ij} + \beta_{12}P_{ij} + \beta_{13}P_{i-1\,j} + \epsilon_{ij} \quad \text{2-4}$$

$$A_{ij} = \beta_{21}B_{ij} + \beta_{22}P_{ij} + \beta_{23}P_{i-1\,j} + \epsilon_{ij} \quad \text{2-5}$$

$$E_{ij} = \beta_{31}B_{ij} + \beta_{32}P_{ij} + \beta_{33}P_{i-1\,j} + \epsilon_{ij} \quad \text{2-6}$$

From each model, we computed predicted values for Valence ($\hat{V}_{ij}$), Arousal ($\hat{A}_{ij}$), and Effort ($\hat{E}_{ij}$). Then we subtracted them from the original ratings to yield adjusted residuals (i.e., Valence ($\tilde{V}_{ij}$), Arousal ($\tilde{A}_{ij}$), and Effort ($\tilde{E}_{ij}$) values independent of fatigue and performance) such that:

$$\tilde{V}_{ij} = V_{ij} - \hat{V}_{ij} \quad \text{2-7}$$

$$\tilde{A}_{ij} = A_{ij} - \hat{A}_{ij} \quad \text{2-8}$$

$$\tilde{E}_{ij} = E_{ij} - \hat{E}_{ij} \quad \text{2-9}$$

We then tested whether adjusted effort ratings could be predicted by adjusted arousal and valence, and whether these relationships varied by cognitive strategy. A linear mixed-effects model was fitted:

$$\tilde{E}_{ij} = \beta_0 + \beta_1 \tilde{A}_{ij} + \beta_2 \tilde{A}_{ij} \times S_j + \beta_3 \tilde{V}_{ij} + \beta_4 \tilde{V}_{ij} \times S_j + \beta_5 S_j + U_{sub[j]} + \epsilon_{ij} \quad \text{2-10}$$

where S_j is a between-subject factor of Strategy (Static vs. Rolling or Proactive vs. Reactive), and a random intercept for participant $U_{sub[j]}$ accounts for individual variability and ϵ_{ij} is residual error.

2-3-1-4 Free choice effort

To quantify participants' effort investment beyond the minimum required to "pass" each block, we defined a free choice effort (FCE) index. This metric captures the extent to which individuals exceed the enforced performance threshold and thus serves as a proxy for intrinsic motivation or willingness to exert extra cognitive effort when not strictly necessary.

For each block i, FCE is computed as:

$$FCE_i = \frac{P_i - P_i^{min}}{P^{max} - P_i^{min}} \quad \text{2-11}$$

ms), $P_i^{min} \in \{4,8,12\}$ is the block's required score, and P^{max} is the maximum attainable score per block, which is always 20.

By construction, $FCE_i = 0$ when participants meet exactly the minimum requirement and approach 1 as performance nears perfection. Negative values indicate failure to meet the threshold.

We then averaged FCE_{ij} across all blocks i for each participant j and task, yielding one mean FCE_j. To test whether participants voluntarily exceeded the minimum requirement, we used two-tailed Wilcoxon signed-rank tests against zero, conducted separately for each strategy. This test tells us whether participants to continue or stop exerting cognitive effort above the required score.

2-3-1-5 Cognitive strategies

To test whether the two cognitive strategies differed in reported effort, arousal and valence, and objective performance, we fitted separate linear mixed-effects models for each outcome—Effort, Valence, and Score—with Strategy as the sole fixed effect and participant as a random intercept to account for repeated measures:

$$E_{ij} = \beta_1 S_j + U_{sub[j]} + \epsilon_{ij} \quad \text{2-12}$$

$$P_{ij} = \beta_1 S_j + U_{sub[j]} + \epsilon_{ij} \quad \text{2-13}$$

Where E_{ij} and P_{ij} are reported effort and score on block i for participant j: S_j is the between-subject factor Strategy (Static vs. Rolling for N-back; Proactive vs. Reactive for AX-CPT), $U_{sub[j]}$ is a subject-specific random intercept, and ϵ_{ij} is residual error.

This modelling approach isolates the effect of strategy on each dependent measure while accounting for individual variability. To evaluate pairwise differences between strategies within each task, we applied Tukey's honest-significant-difference post hoc tests (Tukey, 1949), correcting for multiple comparisons across all the dependant variables.

2-3-2 Pupillometry

We used the Eyelink parsing algorithm to identify blinks in the time series. We removed periods starting 200 ms and ending 200 ms after each blink from the analysis. Further, for each recording, we identified outlier time points as those pupil diameters that were beyond three standard deviations from the participant's average, and we removed these time points from the analysis. Last, the pupil diameter of every recording was scaled to the range between 0 to 1 using the equation: $\hat{x}_t = \frac{x_t - x_{min}}{x_{max} - x_{min}}$, where x is the pupil diameter, to normalize values across participants.

From this, we computed for each block the averaged pupil diameter trial time course by parsing the recording into 60 2-seconds long segments locked to each letter onset (trial). In addition, we averaged $\hat{x}_t$ across the 60 trials (that lasts 2 minutes in total in a block) to arrive at average pupil $\hat{x}_{ij}$ of block i for participant j.

To examine the relationship between subjective ratings of Effort and pupil size the following model that consists of Difficulty level (D_{ij}) and Block number (B_{ij}) as a fixed effect, and Subject number ($U_{sub[j]}$) as random variables was applied for each task separately.

$$\hat{x}_{ij} = \beta_0 + \beta_1 E_{ij} + \beta_2 E_{ij} \times S_j + \beta_3 S_j + \beta_4 D_{ij} + \beta_5 B_{ij} + U_{sub[j]} + \epsilon_{ij} \qquad 2\text{-}14$$

2-3-3 EEG

2-4-3-1 Preprocessing

Pre-processing was carried out using Brainstorm (Tadel et al., 2011) using scripting mode to ensure replicability and provide reusable material. For each participant, the power spectrum density was estimated to control for the overall quality of the recording and to identify bad channels, as channels with abnormal power spectrum density patterns (i.e., excessively high power across all frequencies, flat, or spikes in unexpected frequency bands). After bad channel rejection, the continuous data was inspected to identify segments of data containing artifacts (e.g. muscle activity, movements, except eye blinks). Signals were offline re-referenced to the average of the mastoids. Continuous data was then band-pass filtered between 0.25 and 95 Hz, and a 50 Hz notch filter was applied. After marking the bad segments, 32 components of Picard Independent Component Analysis (ICA) on the continuous recording applied to remove artifacts from blinks and eye movements.

The experiment setup controlled for clicks motor responses made by participants as their number is about the same for each condition (~ 150 per difficulty level per recording session). This was done by having a smaller number of low difficult blocks (a greater number of clicks) than high difficult blocks (a smaller number of clicks).

2-4-3-2 Evoked response potential analysis

First, to ensure precise timing of the triggers sent by the stimulation computer and the display of letters on the stimuli monitor, we installed two photocell sensors on the right and left sides of the monitor. During preprocessing, we adjusted the trigger timing using the average readings from these sensors to mark stimuli onset with millisecond precision. Then, we segmented the EEG signal into 2 seconds long epochs starting 500

ms before each letter stimulus. Epochs were averaged across all trials for each block. The decision of the precise time period domain for the local peaks of different components (e.g. P3) was made post-hoc and after observing the grand average across all blocks of all participants.

2-4-3-3 Stimuli-locked P3 of Cz electrode

To examine the relationship between cognitive effort with the P3, we computed for each block the averaged amplitude from the Cz electrode trial time course by parsing the recording into 60 2-seconds long segments locked to each letter onset (trial) to arrive at the evoked response potential ($P3_i$ of block i). Then within the period of 0.32 to 0.36 seconds of the $P3_i$, the highest amplitude that is not located on the start nor the end of the period was extracted to identify the local peak. Finally, $P3_{ij}$ of block i for participant j was examined in the model below, where E_{ij} is the self-reported Effort, is the S_j is the between-subject factor Strategy (Static vs. Rolling for N-back; Proactive vs. Reactive for AX-CPT), D_{ij} is the Difficulty level, $U_{sub[j]}$ is Subject number as random variables and ϵ_{ij} is residual error.

$$P3_{ij} = \beta_0 + \beta_1 E_{ij} + \beta_2 S_j + \beta_3 E_i \times S_j + \beta_4 D_{ij} + \beta_5 B_{ij} + U_{sub[j]} + \epsilon_{ij} \qquad 2\text{-}15$$

2-4-3-4 Feedback-locked FRN of FCz electrode

The analysis of the FRN is limited only the 2-back and 3-back difficulty level of the N-back task. Because only the blocks of these difficulty levels had failures: blocks when the acquired score was less than the required score. We first computed, for each individual, the average traces between 200 ms and 400 ms relative to feedback screen presentation (when the score is displayed with the failure or pass message) separately

for success and fail blocks for 2-back and 3-back conditions separately. From this we computed the difference between success and fail averaged epochs. Then we tested whether the average amplitude over [200,400] ms of these success-fail differences of 2-back and 3-back significantly differ from each other and in which direction using two-sided one-sample paired t-test.

2-4-3-5 Response-locked ERN of FCz electrode

To analyse the response locked evoked potential, we extracted 1000 ms long epochs time-locked to the responses, that is hits and false alarms with 500 ms pre and post response. We averaged these responses across blocks for each participant. The ERN component was identified separately for the hits and false alarm as the average amplitude of FCz electrode between 0 to 50 ms of response. Finally, we used two-sided one-sample t-test to test the difference of hits and false alarm conditions in each strategy across all trials and all participants.

2-4 Results

2-4-1 Behavioural

Figure 2-4 shows the kernel density of the raw self-reported ratings for each task and strategy.

The self-reported rating of effort in the proactive strategy shows a relatively low mean (25.6) and median (22.8), with SD = 20.5 and a positive skew (0.925), indicating that most participants reported low effort, though some rated higher. The reactive strategy has a similarly low mean (21.6) and median (16.8) but with slightly less variability (SD = 18.4), and a positive skew (0.879), suggesting that effort ratings were generally lower

but still variable. The rolling strategy, in contrast, has the highest mean (74.7) and median (82.4), with a negative skew (-1.25), indicating that most participants reported high effort, though with significant variation (SD = 23.6). The static strategy shows moderate self-reported effort (mean = 60.5, median = 65.5), with a negative skew (-0.725) and moderate variability (SD = 24.1), suggesting that effort ratings were more evenly spread but still on the higher end of the scale.

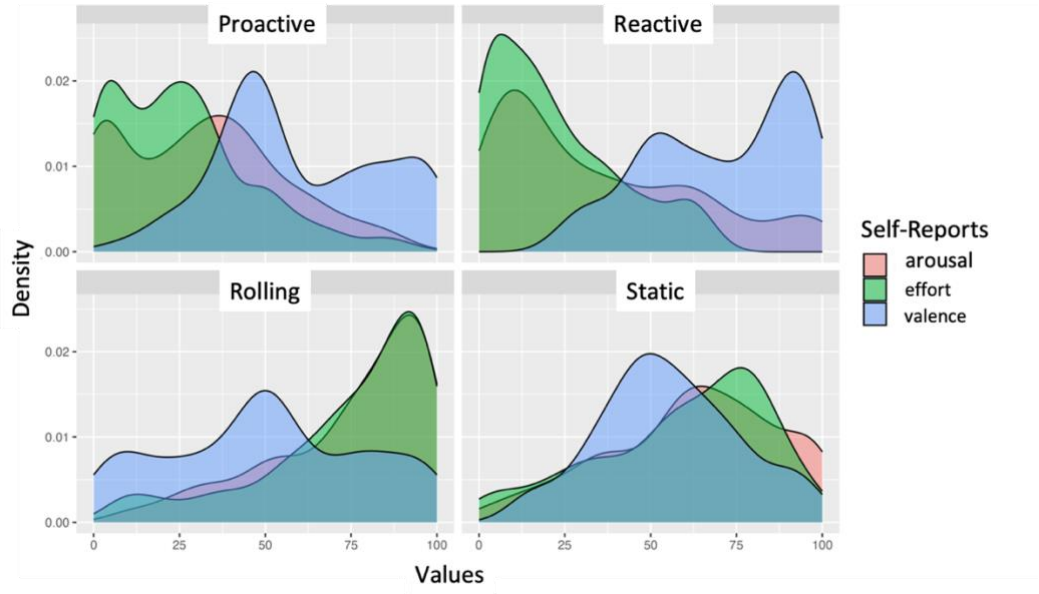

Figure 2-4: Overview of the kernel distribution of the raw self-reports of effort, valence and arousal across all strategies. When comparing N-back task to the AX-CPT task, we can see that the skewness of reported effort and arousal shifts from right to left while reported valence stays almost symmetric in all cases.

The self-reported arousal ratings in the proactive strategy shows relatively low arousal (mean = 32.0, median = 31.9) with low skewness (0.399) and moderate variability (SD = 23.6), suggesting a fairly symmetrical distribution of modest arousal levels. The reactive strategy displays a slightly higher mean (34.7) but a notably lower median (26.6), along with greater variability (SD = 28.9) and higher positive skewness (0.763), indicating that while many participants reported low arousal, a subset reported much higher values. In contrast, the rolling strategy shows the highest arousal levels (mean

= 74.2, median = 80.7) with a negative skew (-1.00), suggesting that most participants reported high arousal with some lower outliers, despite relatively low variability (SD = 22.9). The static strategy also reflects high arousal (mean = 62.2, median = 65.0), moderate variability (SD = 25.1), and mild negative skew (-0.437), indicating generally elevated arousal ratings with fewer extremely low values.

The self-reported valence ratings in the proactive strategy shows moderately positive valence (mean = 59.8, median = 51.1) with low skewness (0.124) and moderate variability (SD = 24.0), suggesting a relatively symmetric distribution but with individual differences in emotional tone. The reactive strategy has the highest mean valence (70.7) and a slightly higher median (73.1), indicating a generally more positive emotional experience; it also shows a mild negative skew (-0.386), suggesting a concentration of high ratings with fewer low outliers. The rolling strategy displays the lowest mean valence (50.1) and median (50), along with the highest variability (SD = 28.4) and nearly no skew (0.0024), reflecting a wide and balanced spread of emotional responses. The static strategy shows moderately positive valence (mean = 55.3, median = 53.8), low skewness (0.103), and the lowest standard deviation (20.4) among all strategies, indicating a more consistent but slightly lower emotional positivity than the reactive strategy.

2-4-1-1 Effort correlates with response time

We first tested whether reported effort could explain response time (recorded for hits and false alarms), using mixed model, controlling for difficulty and time on task (block number). In the N-back task, self-reported effort had a significant positive main effect on mean RTs (β ± SE = 1.288e-03 ± 1.855e-04, t = 6.944, P = 8.53e-12), indicating that higher effort is associated with longer RTs. Task block had a significant negative effect (β ± SE = -3.715e-03 ± 3.742e-04, t = -9.928, P < 2e-16), suggesting a decrease in RTs over the course of the task probably as the result of habituation and learning. Further the interaction between effort and strategy was positive (β ± SE = 9.756e-04 ± 2.764e-

04, t = 3.530, P = 0.000442) meaning that changes in self-reported effort are associated with larger RT in static than in rolling.

We conducted the same analysis separately in the AX-CPT task. Self-reported effort had no significant effect on mean RTs (β ± SE = 2.614e-04 ± 2.144e-04, t = 1.219, P = 0.223244) but difficulty level had a significant positive effect on RTs (β ± SE = 2.167e-02 ± 5.181e-03, t = 4.181, P = 3.26e-05). Similar to N-back, the effect of habituation was seen (β ± SE = -1.175e-03 ± 3.026e-04, t = -3.882, P = 0.000115). And the RTs of reactive strategy were larger (β ± SE = 5.975e-02 ± 3.289e-02, t = 1.219, P = 0.079181), with no interaction with difficulty.

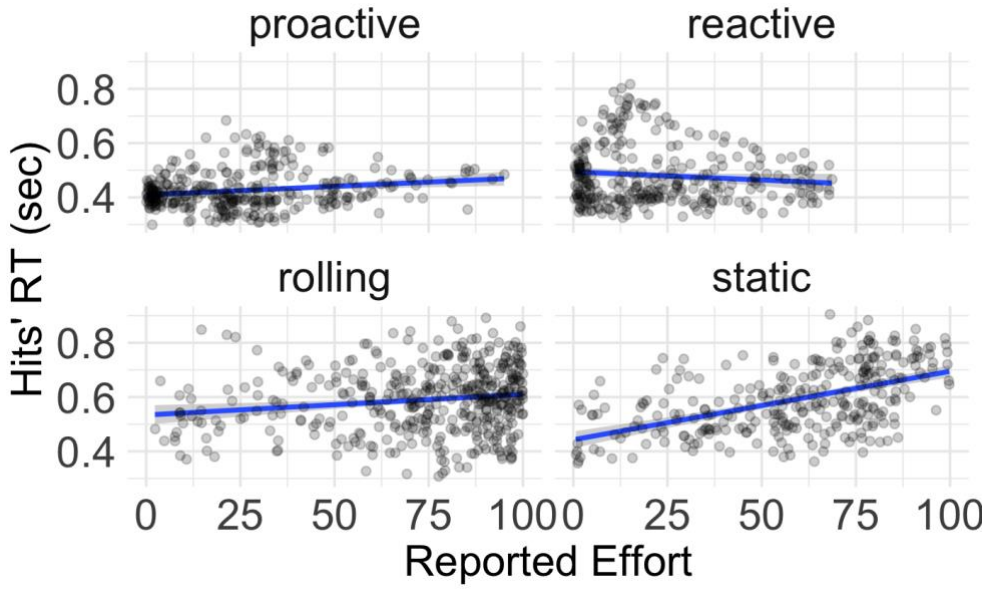

Figure 2-5: Predicted reaction times of clicks only in Hit trials as a function of self-reported effort ratings, shown separately for the cognitive strategies. Lines represent the estimated marginal effects of effort across different strategies (proactive, reactive, rolling, static), based on linear mixed-effects models controlling for difficulty level and block number with random intercepts for participants. Shaded areas indicate 95% confidence intervals around the predictions.

2-4-1-2 Effort correlates with arousal not with valence

We examined how self-reported effort was associated with both valence and arousal using a linear mixed model. In this analysis we first regressed out the effects of performance and task progression from all the self-reported ratings (see the section 2.4.2).

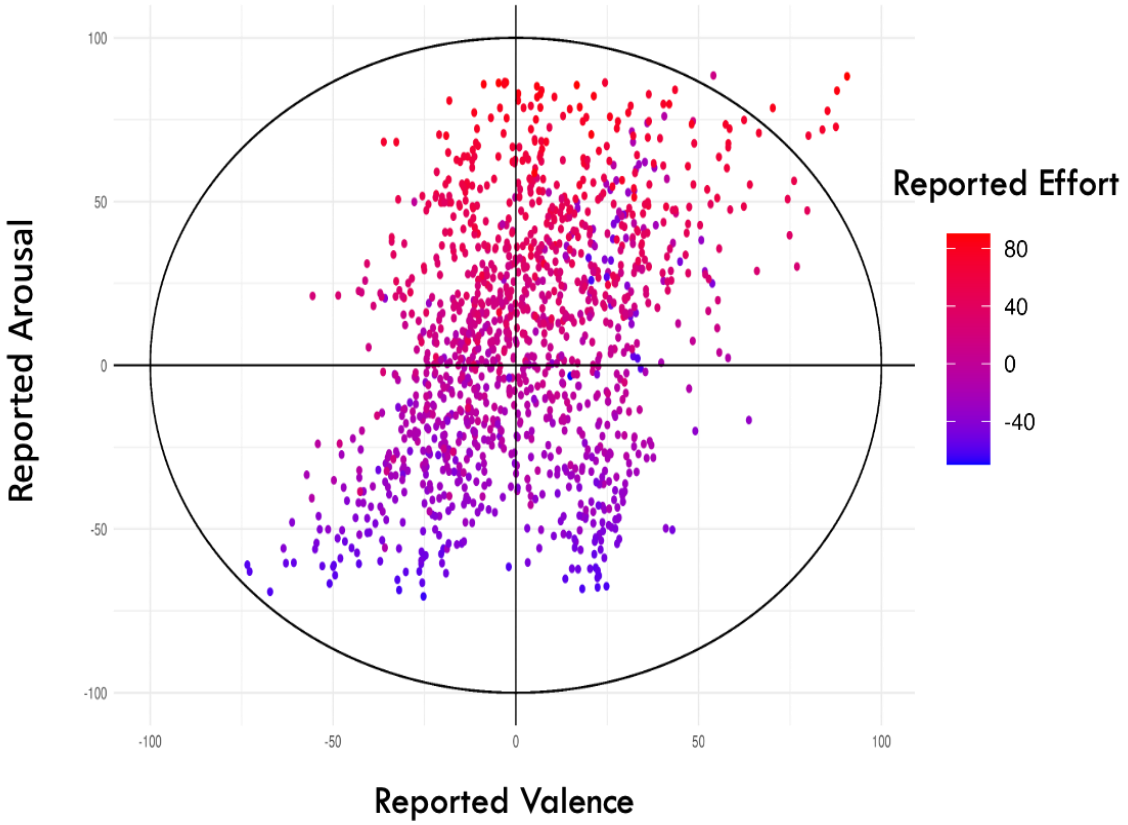

Figure 2-6: Relations between the three self-reports scales after adjustment for block number (time-on-task) and score for all the self-reports. Each point represents self-report from one block (reported valence, reported arousal, reported effort). The valence and arousal dimensions are shown in the x and y axis respectively and the effort dimension is colour coded (blue= low effort; red= high effort). You can see that reported effort increases in vertical (arousal) and not in the horizontal (valence) dimension.

The results show that arousal had a strong and significant positive effect on effort (β = 0.90, SE = 0.03, t = 29.77, P < 0.001), indicating that higher levels of arousal were strongly associated with increased effort. In contrast, the effect of valence was not significant (β = 0.07, SE = 0.04, t = 1.82, P = 0.07). These findings highlight the dominant role of arousal in subjective effort, with valence having a comparatively minor to no association. There was no interaction with strategy.

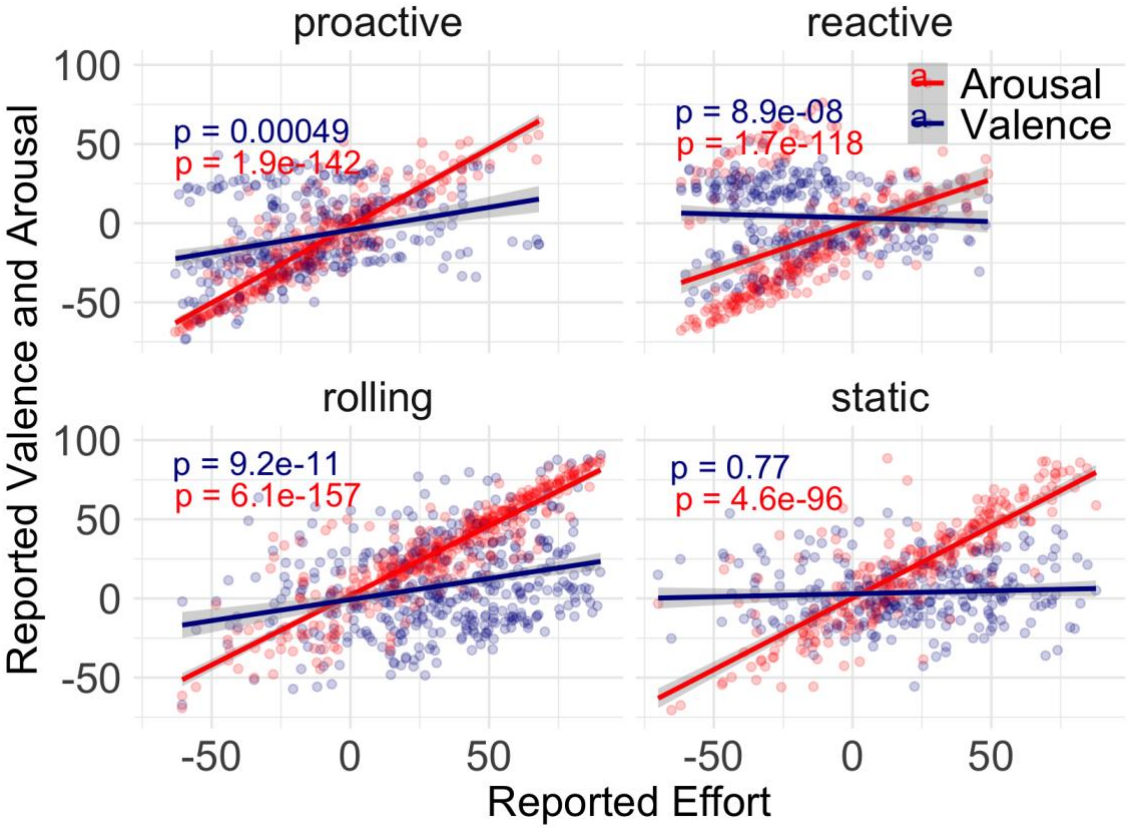

Figure 2-7: This figure is showing you another way of illustrating the same result shown in the figure 5a. Here the x-axis is the adjusted reported effort, and the y-axis are adjusted reported arousal and valence (colour coded). For all the strategies across both tasks, you can see the positive correlation between the adjusted reported effort with the adjusted reported arousal while there is no correlation between the adjusted reported effort and the adjusted reported valence at 5 percent confidence interval.

2-4-1-3 Free Choice of Effort (FCE) is greater than zero

We analysed the averaged FCE per participant separately for each task and strategy. The Wilcoxon test showed that FCE is above zero in the proactive strategy (V = 1035, p-value = 4.965e-09), reactive strategy (V = 903, p-value = 1.674e-08), the rolling strategy (V = 1035, p-value = 5.34e-09) and in the static strategy (V = 666, p-value = 1.746e-07). In addition, we observed that FCE did not change as a function of the required score (Figure 2-8).

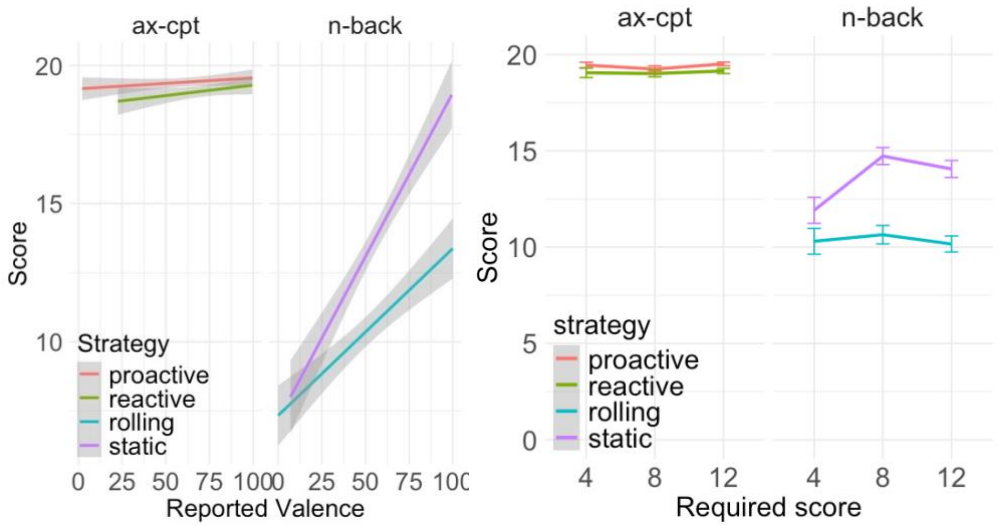

Figure 2-8: The left figure (panel A) presents to you the correlation between raw reported valence and score for all cognitive strategies across two tasks. Participants report valence before score feedback presentations. The correlation is coherent with participant's claim in the posts-experiment interviews that they were able to predict their score beforehand. The right figure (panel B) displays the mean scores and their associated standard error bars for each required score, aggregated across all strategies and both tasks. The data indicate no correlation between the required score and the actual score achieved. This finding contradicts the hypothesis that participants aimed for the required score but consistently exceeded it, as the observed scores remain approximately centred around the average values across all conditions.

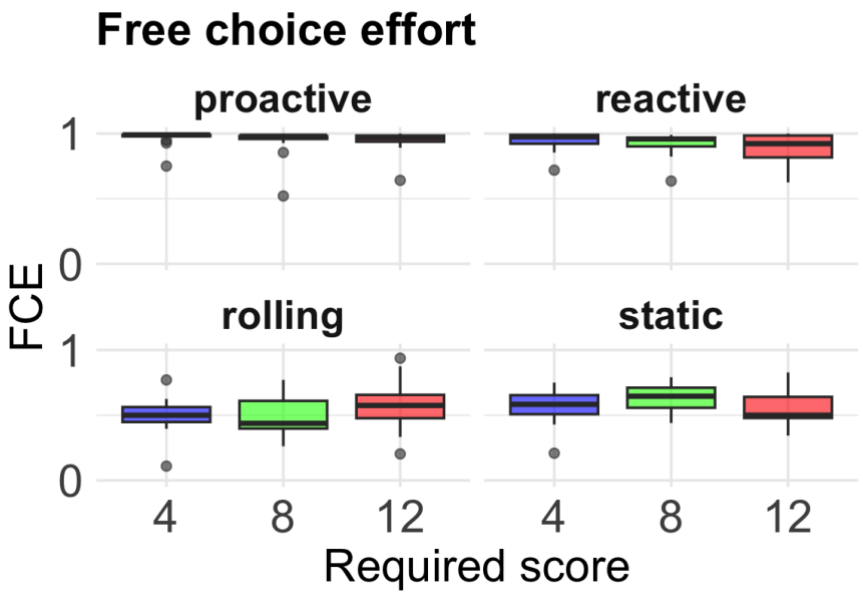

Figure 2-9: This figure is presenting you "free choice effort" (FCE) as y-axis by required score as the x-axis. You can see that FCE of participants in both cognitive strategies across the two tasks is significantly above zero no matter what the required score is.

2-4-1-4 Within difficulty level, score has no relation with effort

To analyse the relationship between effort and performance we divided the dataset for each cognitive strategies as a function of the difficulty levels. For each difficulty level we then tested whether performance could be predicted by effort taking into account the block number (time on task). For the rolling strategy, the mixed model analysis revealed that neither slider effort response nor the number of blocks significantly associated with performance. Specifically, the estimate for slider effort response was ($\beta \pm SE = 0.00059 \pm 0.00101$, $t = 0.59$, $P = 0.562$), and the estimate for the number of blocks was ($\beta \pm SE = -0.00168 \pm 0.00242$, $t = -0.70$, $P = 0.489$). The intercept was significant ($\beta \pm SE = 0.802 \pm 0.066$, $t = 12.10$, $P < 0.001$), indicating a baseline level of performance that differed across participants. In the analysis of difficulty level set to 2 (i.e. 2-back), the number of blocks significantly influenced performance ($\beta \pm SE = 0.00434 \pm 0.00147$, $t = 2.96$, $P = 0.0037$). There was no effect of self-reported effort (β

± SE = -0.00082 ± 0.00084, t = -0.97, P = 0.334). The intercept was significant (β ± SE = 0.429 ± 0.072, t = 5.95, P < 0.001). These results suggest that, within difficulty level 2, task progression had a significant positive impact on performance, while effort did not associate with score. The effect was very small though. The analysis of the 3rd difficulty level showed that the number of blocks significantly influenced performance (β ± SE = 0.00525 ± 0.00101, t = 5.19, P < 0.001). However, slider effort response did not significantly affect performance (β ± SE = -0.00056 ± 0.00081, t = -0.70, P = 0.487). The intercept was also significant (β ± SE = 0.228 ± 0.074, t = 3.09, P = 0.0025), indicating a baseline level of performance. These results suggest that task progression has a significant impact on score at difficulty level 3, while effort does not appear to play a significant role in the model.

strategy	***Difficulty Level***	***Average D-prime***
proactive	1	3.83
proactive	2	4.03
proactive	3	4.01
reactive	1	3.86
reactive	2	3.88
reactive	3	3.91
rolling	1	3.41
rolling	2	2.01
rolling	3	1.18
static	1	3.48
static	2	1.72
static	3	2.12

Table 2-3 : Performance of each strategy based on d-prime. The maximum d-prime is 4.03 and minimum 0. Hit rate and false alarm rate are calculated with log-linear correction to avoids infinite z-scores when hit or false alarm rates are 0 or 1.

The linear mixed model analysis for the static strategy with difficulty level set to 1 showed that neither slider effort (β ± SE = 0.00049 ± 0.00129, t = 0.38, P = 0.706) nor the number of blocks (β ± SE = 0.00155 ± 0.00290, t = 0.54, P = 0.595) significantly influenced performance. The intercept was significant (β ± SE = 0.777 ± 0.0637, t = 12.21, P < 0.001), indicating a baseline level of performance. These results suggest that, at difficulty level 1, neither effort nor task progression had a significant

effect on performance. With difficulty level set to 2, we see that both slider effort (β ± SE = -0.00291 ± 0.00114, t = -2.56, P = 0.012) and the number of blocks (β ± SE = 0.01114 ± 0.00208, t = 5.36, P < 0.001) significantly influenced performance. Specifically, slider effort was negatively associated with performance, while the number of blocks had a positive impact on performance. The intercept was also significant (β ± SE = 0.554 ± 0.087, t = 6.35, P < 0.001), indicating a baseline level of performance at difficulty level 2. These results suggest that effort and task progression both correlate with performance. The analysis for the difficulty level set to 3 showed that slider effort (β ± SE = 0.00225 ± 0.00109, t = 2.07, P = 0.042) and the number of blocks (β ± SE = 0.00623 ± 0.00175, t = 3.57, P < 0.001) slightly but significantly influenced performance. Specifically, an increase in slider effort was associated with a small increase in performance, while the number of blocks also positively impacted performance. The intercept was significant (β ± SE = 0.2207 ± 0.0874, t = 2.53, P = 0.014), indicating a baseline level of performance at difficulty level 3. These findings suggest that both task progression and effort are associated with small changes in performance at this difficulty level.

The linear mixed model analysis for the proactive strategy across three difficulty levels (1, 2, and 3) revealed that neither slider effort nor the number of blocks is significantly associated with performance at any difficulty level. At all levels, the intercept was significant (P < 0.001), indicating a stable baseline performance. At difficulty levels 1, 2, and 3, performance remained consistent, with no significant effects from effort or task progression. These results suggest that, regardless of difficulty level, effort and task progression have no significant relationships with performance. Further, the linear mixed model analysis at three difficulty levels (1, 2, and 3) for the reactive strategy revealed that neither self-reported effort nor the number of blocks significantly correlate with performance at any difficulty level. At difficulty levels 1, 2, and 3, the intercepts were all significant (P < 0.001), indicating a stable baseline performance. These results suggest that, regardless of difficulty, effort and task progression did not significantly impact performance.

Overall, the findings from both the proactive and reactive strategy analyses align with the previous results across the rolling and static strategies, indicating that score is independent of self-reported effort. Despite the significant baseline levels of score in each strategy, variations in self-reported effort did not significantly correlate with performance. This consistency across different strategies highlights that by increasing the difficulty level the effort needed to perform the task increases and the performance decreases as indicated by the baseline intercepts of the models (figure 2-10). However, for a given difficulty level, our results suggest that no relationship exists between self-reported effort and performance.

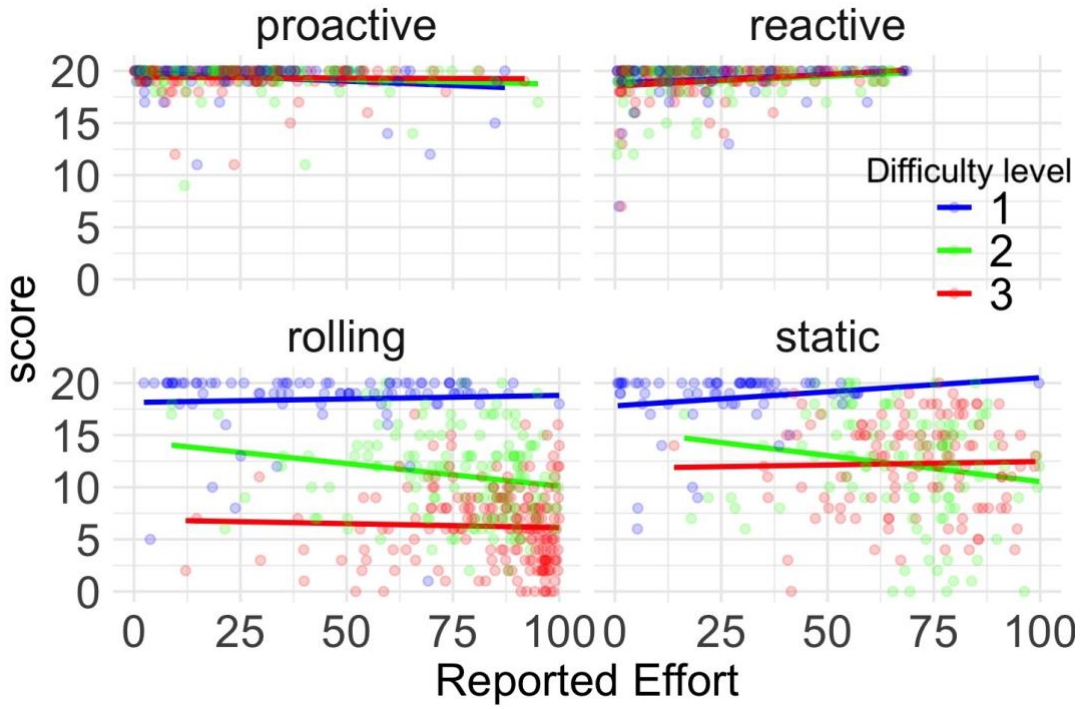

Figure 2-10: This figure is presenting you the relationship between score and reported effort in both cognitive strategies of both tasks. You can see that as difficulty level gets harder, the score decreases and at the same time reported effort increases. However, within difficulty level there is no relationship between reported effort and score.

2-4-1-5 Higher score with less effort in static compared to rolling

The Tukey's honest-significant-difference post hoc tests of the mixed models (see section 4-1) revealed that the rolling strategy (β = 73.05) required considerably more effort than the static strategy (β = 59.07), suggesting that the rolling strategy was significantly more effortful (P=0.0171). The proactive strategy (β = 25.81) was slightly reported as more effortful than the reactive strategy (β = 21.96), although not significantly (P = 0.8196).

Moreover, in the N-back task, score was significantly influenced by the different strategies (P<0.0001). The rolling strategy (β = 2.82) had lower performance score than static (β = 3.71). However, the proactive strategy (β = 6.16) resulted in higher scores than the reactive strategy (β = 5.88) whose difference, however, was not significant (P=0.4061).

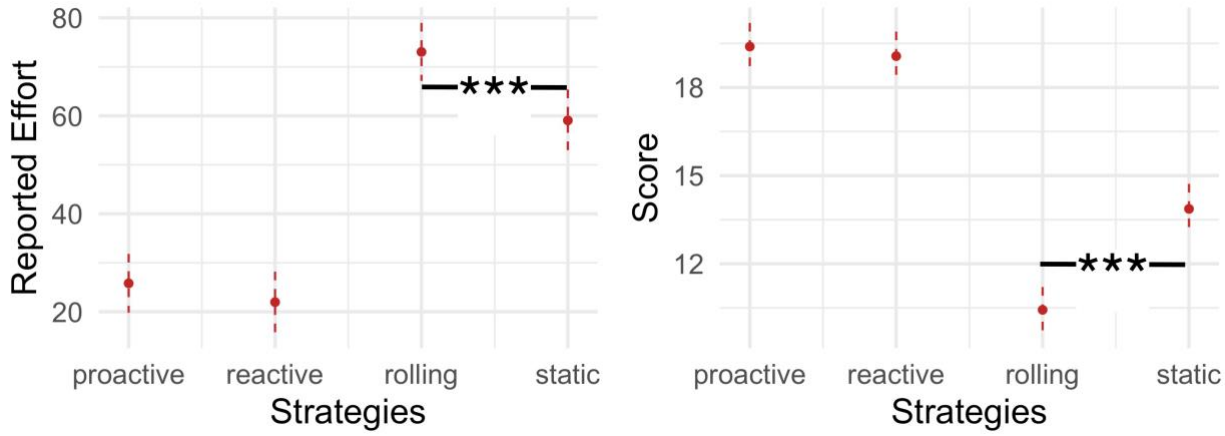

Figure 2-11: Comparison of mean effort ratings (left) and score (right) between the cognitive strategies. The red dots are averages across blocks and participants and the dashed lines are the standard error. In the N-back task, you can see that the reported effort is significantly higher in the rolling than the static strategy (according to the Tukey's honest-significant-difference post hoc tests). Yet, the score is significantly lower in the rolling than the static strategy. We interpret this result as static being a "smarter" strategy than rolling. Because static can deliver higher performance with lower effort.

In the N-back task the rolling strategy (β = 49.88) had lower valence ratings, while the static strategy (β = 56.56) resulted in higher valence, although their difference was not significant (P=0.2598). And in the AX-CPT reactive strategy (β = 70.66) elicited higher valence ratings, than proactive strategy (β = 59.81), although their difference was not significant either (p=0.6581). See figure 2-11 for a summary.

2-4-1-6 Complementary relationship between effort and strategy to influence performance

The linear mixed model analysis for the N-back task showed that the N-back level of difficulty significantly reduced performance (β = -0.172, SE = 0.011, t = -15.84, P < 0.001), and reported effort was also associated with decreased performance (β = -0.00268, SE = 0.00046, t = -5.85, P < 0.001). Compared to the rolling strategy as the reference category, the static strategy alone did not significantly influence performance (β = -0.0516, SE = 0.047, t = -1.10, P = 0.274). However, the interaction between the static strategy and effort was significant and positive (β = 0.00212, SE = 0.00058, t = 3.68, P < 0.001). This suggests that the static strategy moderates the effect of effort on performance, with higher self-reported effort being associated with improved performance when the static strategy is used, in contrast to the rolling strategy. For instance, in the 3-back the score is higher in static than in the rolling cognitive strategy.

Specifically, the positive interaction suggests that in the static strategy, as self-reported effort increases, performance improves more than it does under the rolling strategy. In other words, when difficulty level increases and consequently the reported effort increases while performance decreases, this negative relationship is weaker when the static strategy is used compared to the rolling strategy, implying that using the static strategy would help mitigate the detrimental effect of higher effort on performance. The interaction thus highlights a moderation effect, where the static strategy changes the magnitude of the association between effort and performance. In the static strategy as compared to the rolling, the negative association of effort with performance is

reduced, meaning that the strategy itself plays a crucial role in how effort is associated with task performance. In sum, the findings show that the static strategy weakens the negative link between effort and performance compared to the rolling strategy. As effort increases with task difficulty, performance drops less sharply under the static strategy, suggesting it helps buffer against the detrimental effects of higher effort. This indicates that the strategy itself moderates how effort relates to performance.

In the AX-CPT, task the model contrary to our expectations shows a significant negative effect of effort (β ± SE = -3.631e-03 ± 2.552e-04, t = -14.227, P < 2e-16). As well, difficulty level has a significant negative effect (β ± SE = -3.256e-03 ± 2.182e-04, t = -14.924, P < 2e-16). The task prolongation has significant negative coefficient (β ± SE = -4.452e-03 ± 3.278e-05, t = -135.813, P< 2e-16). The interaction between effort and the static strategy was significant (β ± SE = -1.868e-02 ± 3.513e-04, t = -53.176, P < 2e-16), suggesting that the relationship between effort and performance was more pronounced for the proactive strategy compared to the reactive strategy.

2-4-2 Pupillometry

2-4-2-1 Positive correlation between pupil size and effort

We ran a mixed model regression on the average pupil size of a block against reported effort interaction with the cognitive strategy, and difficulty level, block number as the predictors and with random intercept for individuals.

In the N-back task the model shows a significant positive effect of effort (β ± SE = 6.446e-03 ± 1.602e-04, t = 40.224, P < 2e-16), indicating, as expected, that increased self-reported effort was associated with larger pupil size for both strategy groups. As well, difficulty level has a significant positive effect (β ± SE =8.490e-03 ± 3.462e-04, t = 24.522, P < 2e-16). The task prorogation has significant negative coefficient (β ± SE

= -5.972e-03 ± 2.750e-05, t = -217.170, P< 2e-16). The interaction between effort and the static strategy was significant (β ± SE = -5.101e-03 ± 2.030e-04, t = -25.129, P < 2e-16), suggesting that the relationship between effort and pupil size was more pronounced for the rolling strategy compared to the static strategy.

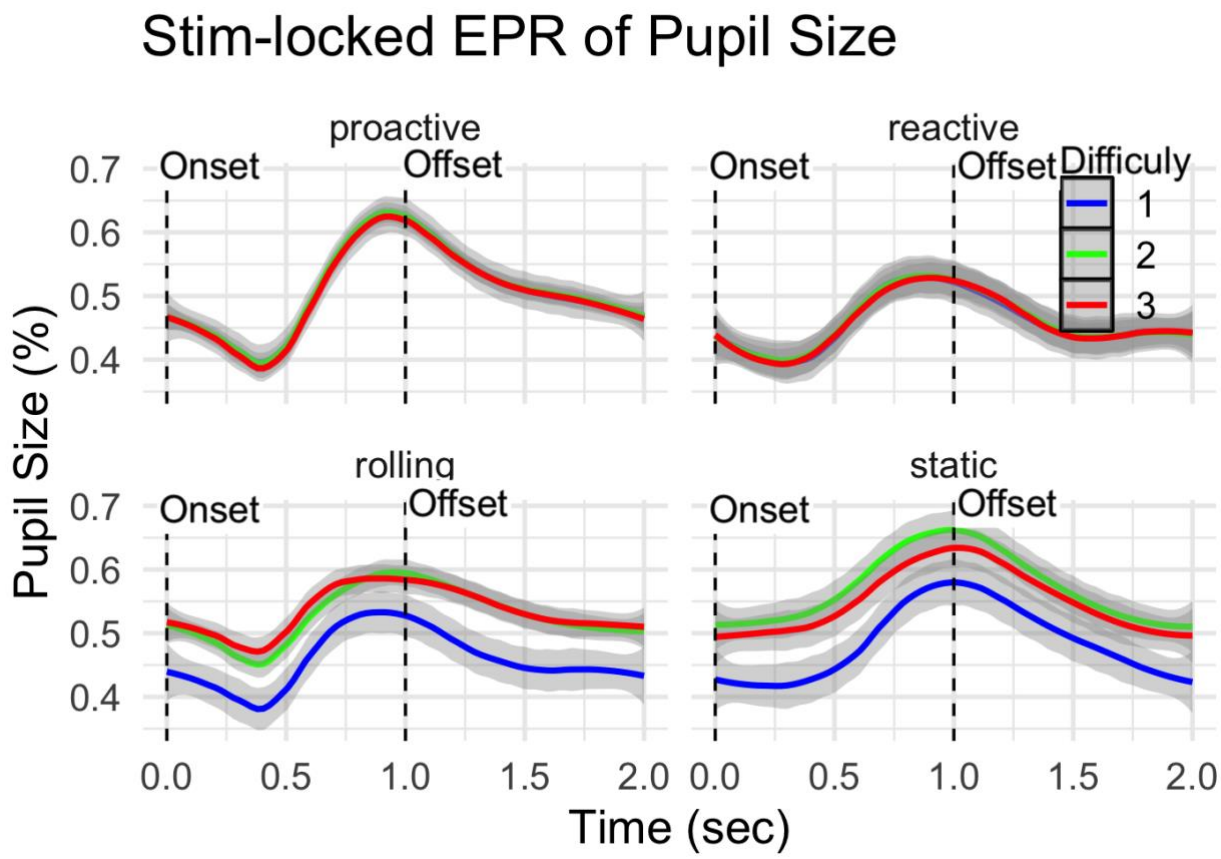

Figure 2-12: This figure presents to you the task-evoked pupillary response (EPR). The time zero is trial onset and 1 second is the stimulus offset. The colours represent the EPR of different difficulty level for the four cognitive strategies, proactive and reactive on the top for of the AX-CPT task and rolling and static on the bottom for the N-back task. The EPR is higher for the more effortful difficulty level. To plot the result, we employed a local polynomial regression algorithm, also known as moving regression for smoothing and removing spikes in creating the figures (Cleveland et al., 1988).

In the AX-CPT task the model contrary to our expectations shows a significant negative effect of effort (β ± SE = -3.631e-03 ± 2.552e-04, t = -14.227, P < 2e-16). As well,

difficulty level has a significant negative effect (β ± SE = -3.256e-03 ± 2.182e-04, t = -14.924, P < 2e-16). The task prolongation has significant negative coefficient (β ± SE = -4.452e-03 ± 3.278e-05, t = -135.813, P< 2e-16). The interaction between effort and the static strategy was significant (β ± SE = -1.868e-02 ± 3.513e-04, t = -53.176, P < 2e-16), suggesting that the relationship between effort and pupil size was more pronounced for the proactive strategy compared to the reactive strategy.

2-4-3 EEG

2-4-3-1 Positive correlation between P3 and difficulty level

We ran a mixed model regression on the amplitude of P3 with reported effort interaction with the cognitive strategy, difficulty level, block number as the predictors and with random intercept for individuals.

In the N-back task, self-reported effort did not significantly predict P3 (β ± SE = -1.347e-09 ± 4.109e-09, t = -0.328, P = 0.7473). However, task difficulty significantly influenced P3 amplitude positively (β ± SE = 2.494e-07 ± 9.385e-08, t = 2.657, P = 0.0171). Additionally, the task block showed a positive effect (β ± SE = 1.565e-08 ± 6.698e-09, t = 2.336, P = 0.0326). And no significant effect was observed for strategy.

The same was true for the AX-CPT task, where no significant effect of self-reported effort was seen (β ± SE = -2.201e-09 ± 6.559e-09, t = -0.336, P = 0.7432). However, task difficulty significantly influenced P3 amplitude positively (β ± SE = 2.220e-07± 7.102e-08, t = 3.126, P = 0.0091). Additionally, the task block showed a negative effect (β ± SE = -2.840e-08 ± 9.840e-09, t = -2.886, P = 0.0141). And no significant effect was observed for strategy.

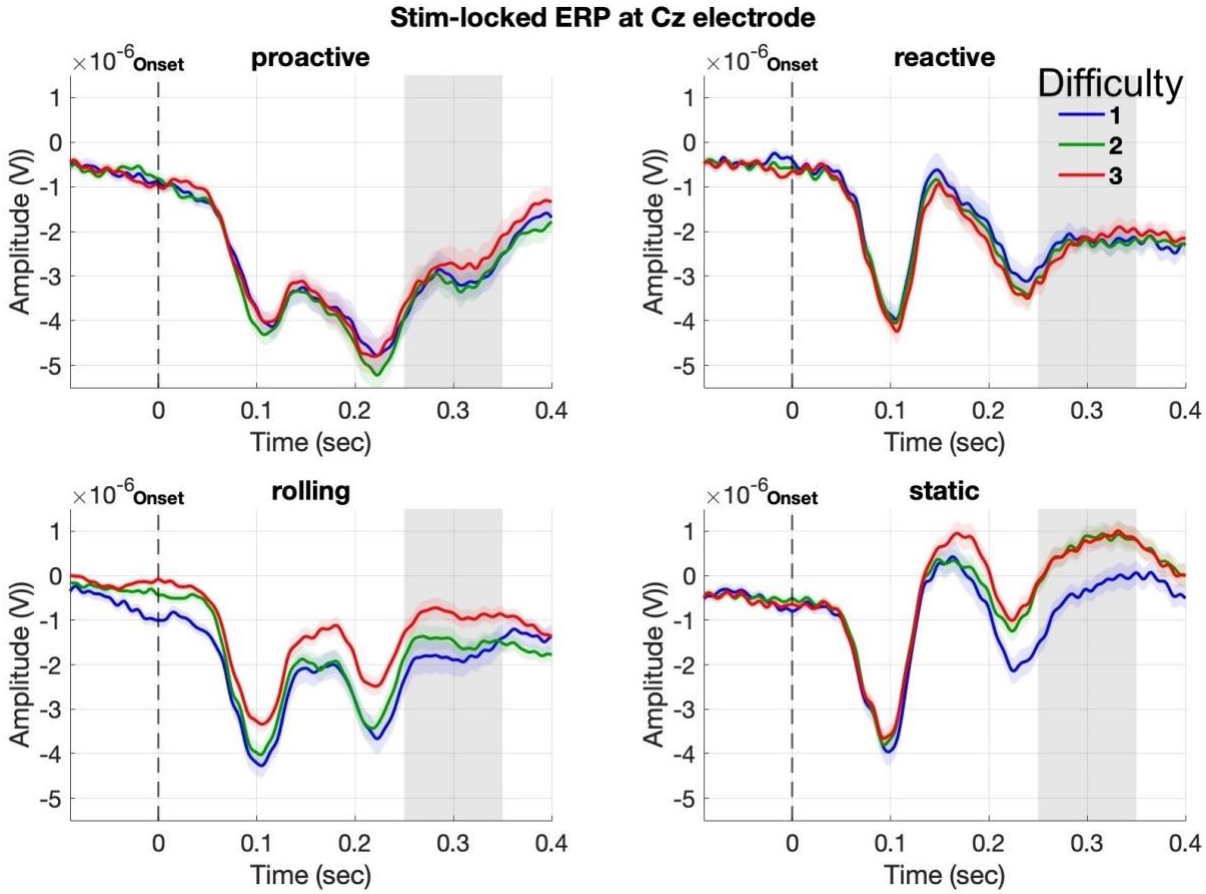

Figure 2-13: Grand averaged stimulus-locked evoke response potentials (ERP) recorded at Cz electrode, separately for the four task-strategy combinations. The colours represent the different difficulty levels. Shaded area represents the time window in which the local peak is extracted to determine P3. You can see that in the N-back task increased difficulty level is associated with the increased in the amplitude of the shaded area (P3).

2-4-3-2 Negative correlation between FRN and difficulty level

The result of two-sided one-sample paired t-test revealed a statistically significant difference between the success and fail difference of 3-back vs the success and fail difference of 2-back ($t(52) = -3.46$, $p = 0.0011$). These findings suggest that the difference of 2-back and 3-back elicited significantly different FRN responses. The FRN response was higher in 3-back than 2-back (figure 2-14).

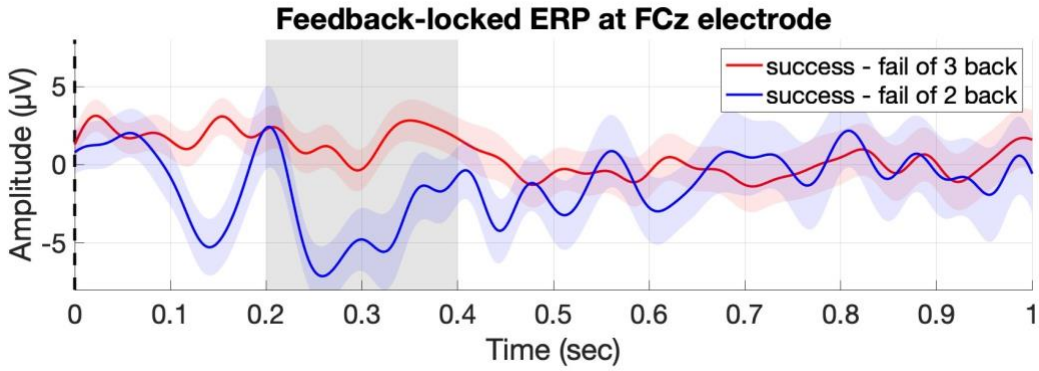

Figure 2-14: Feedback-locked evoked response potential (ERP). The time at zero is the onset of the score feedback. The red line is the difference between success and fail blocks of in the 3-back difficulty level in the N-back task. And the blue line is the difference between the success and fail blocks of the 2-back difficulty level in the N-back task. You can see that the success-fail difference of the more effortful 3-back difficulty level is significantly above the success-fail difference of the less effortful 2-back difficulty level.

2-4-3-3 Negative correlation between ERN and false alarm

A two sided one-sample paired t-test comparing average ERN amplitude of false alarms and hits in the proactive strategy ($t(71.02) = -45.950$, $p < .0001$), reactive strategy ($t(54.01) = -21.340$, $p < .0001$), rolling strategy ($t(519.40) = -27.312$, $p < .0001$), and static strategy ($t(166.51) = -49.170$, $p < .0001$) revealed that ERN was significantly larger (more negative) for the false alarm than the hit.

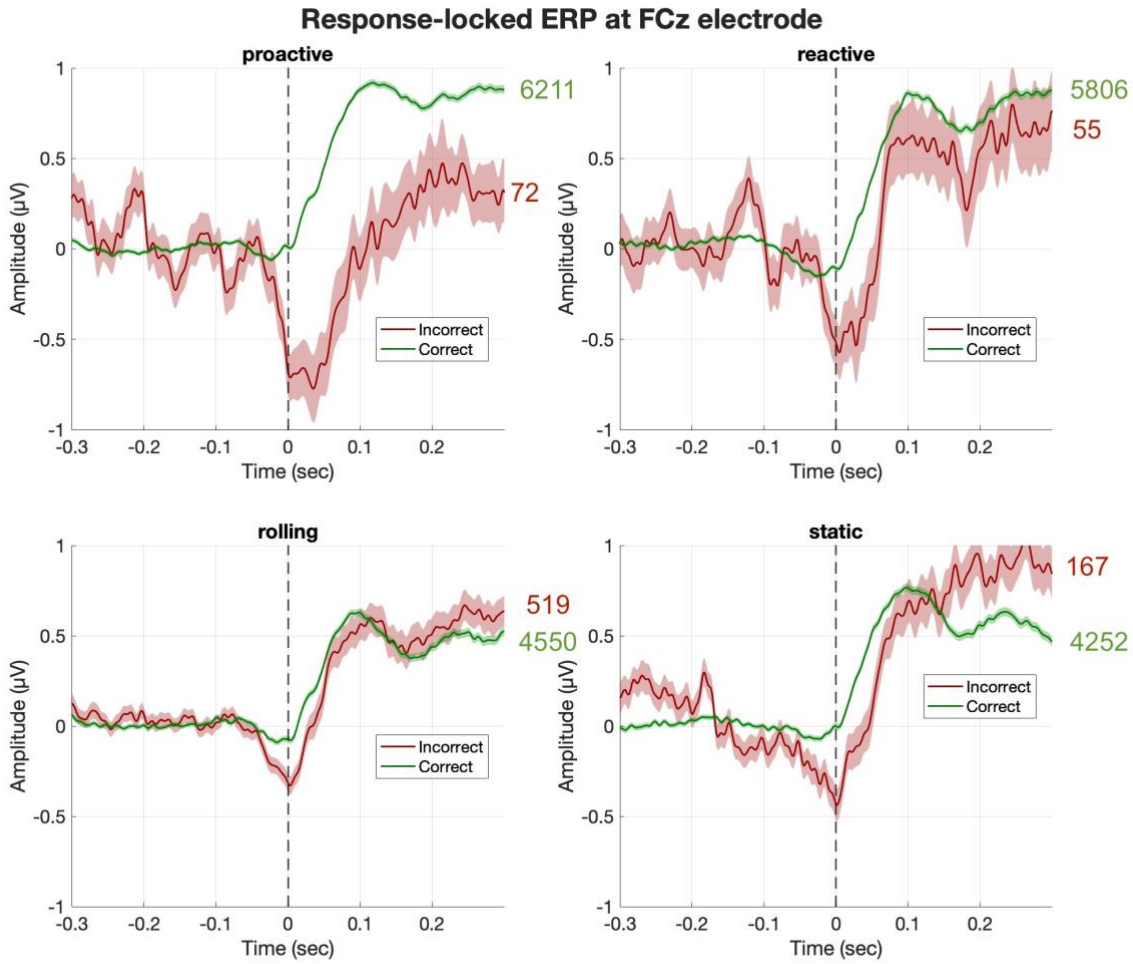

Figure 2-15: This figure presents you the response-locked evoke response potential (ERP). The time at zero is when participants made a click. You can see that when the click is a false alarm (incorrect response, red line) as compared to when it is a hit (correct response, green line) there is a negative deflection almost at the time of response known as ERN. Note that the number of trials stated right to the respective grand average.

2-5 Discussion

The primary goal of this study was to evaluate and compare the two approaches of cognitive effort: arousal and valence in a novel experimental design. These approaches make different predictions regarding the phenomenology, and physiology of cognitive

effort, and its relationship with performance (as illustrated in table 2). The results from our experiment clearly support the predictions made by the arousal approach. We will now discuss each of the findings in turn.

2-5-1 Phenomenology

Regarding the relationships among participants' self-reports, the arousal approach predicted a positive relationship between effort and arousal ratings, while the valence approach predicted a negative relationship between effort and valence ratings. High arousal can be aversive or not, but negative valence is always aversive (Kurzban, 2016; Knutson et al., 2014). For example, an individual may actively seek out high arousal experiences such as skydiving or competitive sports. In contrast, the same physiological arousal may prompt avoidance when associated with perceived threat or conflicts. Thus, high state of arousal is not inherently aversive.

Based on the arousal approach, cognitive effort can sometimes be aversive and sometimes not; it is not inherently a cost. However, based on the valence approach, cognitive effort is always aversive and is therefore an inherent cost. Nevertheless, the sensation of cognitive effort can be associated with both high arousal and negative valence simultaneously; cognitive arousal can be an inherent cost.

Our introspective results showed a strong positive correlation between self-reported effort and arousal, but only a very small positive correlation with valence (with marginal effect close to zero). Therefore, based on introspective reports from participants across two tasks (one intense and one dull) and four cognitive strategies, we can conclude that the arousal approach provides a more accurate representation of cognitive effort. In contrast, there is no indication in this context that judgements of higher cognitive effort are associated with negative valence.

2-5-2 Behavioural

Our behavioural result showed that FCE was significantly above zero. This means that participants continued exerting cognitive effort above the requirements (Figure 2-8). This observation poses the question that, if cognitive effort is aversive and costly, then why participants continued exerting when it could have been avoided. There can be several possible answers to this question.

The first possibility could be that participants were not sure if their score was above the required score. There are three reasons suggesting that this is probably not the case. First, the presence of an identifiable Error Related Negativity suggests that the information about whether they make an error or not is available, in the brain at least (Nieuwenhuis et al., 2001). Secondly, we see a strong relation between reported valence and score, even though the subjective ratings are made before the score feedback was disclosed (figure 2-9 a). Participants reported valence lower when their score was low and reported valence higher when their score was higher; this suggests that they had a good estimation of their score before it being disclosed to them. And thirdly, in the post experiment interviews, we asked participants "Were you able to predict your score?". 28 out of the 28 participants in the AX-CPT task said "yes", and 17 out 28 in the N-back task said "No" to 3-back difficulty level while others said "yes".

A second potential explanation is that participants may have targeted the required scores, but they landed slightly above the thresholds. In other words, they knew their score but to be completely sure that they passed the required score they aim a bit higher. For instance, in the condition requiring a score of 4, participants might have achieved scores of 5 or 6; in the condition requiring a score of 8, scores of 9 or 10; and in the condition requiring a score of 12, scores of 14 or 15. If this hypothesis were accurate, one would expect a positive correlation between the required score and the actual score achieved. However, the data do not support this pattern, as evidenced by the lack of a significant positive correlation shown in Figure 2-9 b.

The third possibility could be that the participants decided to exert effort all along the block because monitoring errors and counting score plus exerting the required effort could have been more effortful. This explanation is probably not the case for two reasons. First, as previously established the participants could predict their score thus, they were exerting effort above the requirement, and they were (at least implicitly) counting score. Second, the error monitoring itself is mostly assumed as an automatic process and usually the automatic processes as compared to cognitive control processes are not experienced subjectively as effortful (Botvinick et al, 2001). These two reasons casts doubt on this explanation.

The fourth possibility is that the intrinsic value of exerting cognitive effort exceeds its intrinsic cost. The relationship between intrinsic and extrinsic motivation on revealed preferences (the observed choice of one option over another) is an active area of research (Fehr and Falk, 2001; Andreoni and Miller, 2002; Bowles, 2016). The dominant view in this literature is to take the net effect of cost-benefit analysis on behaviour into account.

In the current case, the required score did not correlate negatively with either the score or the FCE. This suggests that cognitive effort cannot be said to be inherently costly, as its net effect is not negative (assuming the positive aspect of intrinsic motivation constant). Additionally, this interpretation, in line with the introspection results (i.e. the self-reports, see above) and the physiological results (see below).

2-5-3 Physiology

Pupillometry supported the positive relation between self-reported arousal and self-reported effort. As self-reported effort positively correlated with pupil size, consistent with findings previously reported in the literature (Wel and Steenbergen, 2018). This was especially interesting in the AX-CPT task because of the small variation in self-reported effort and also because this sustained attention task is not particularly

intense. So much so that participants described it as boring and reported low level of arousal (sleepiness). Yet, because of strong effect size of pupil size (Cohen's d > 1) even within these low range of arousal of the AX-CPT task the pupil faithfully dilated with the small variation in the reported effort.

The feedback-related negativity (FRN) deflects more positively to gain than loss (monetary and non-monetary (Brown et al., 2022). FRN has been previously shown to correlate with the probability of choosing a high effort option compared to a low effort option, or with the willingness to exert effort (Bogdanov et al., 2021). In our experiment, we see that FRN's difference of success-fail in the 3-back is higher than in the 2-back difficulty level. This finding is similar to previous studies such as Ma et al., (2014), and Yi et al., (2020) reporting stronger FRN with more effort. If cognitive effort was costly then we would have expected the FRN's difference between success and fail to decrease in 3-back difficulty level that requires more effortful cognitive control. Yet, the results show the contrary.

One interpretation of this could be drawn from Brehm's motivational intensity theory, which posits that the amount of effort *determines* the valence of outcomes. Specifically, this theory assumes that the valence of an outcome, such as success or failure, is not fixed but depends on the amount of effort required to achieve it. A successful outcome after a demanding task may be appraised as more positive (higher positive valence), while the same outcome in an easy task might feel less rewarding. Conversely, failure after high effort could feel more aversive (higher negative valence) than failure with minimal effort. In this framework, effort plays a central role in shaping the perceived value of outcomes, such that the experience of gain or loss is coloured by how much one had to invest to reach (or fail to reach) a goal (Brehm & Wright, 1983).

Contrary to our results, there are also previous studies like, Krigolson et al., (2015) and Gheza et al., (2018) who reported a negative relationship between FRN and difficulty level. Krigolson et al., (2015) induced higher cognitive effort by asking their participants not to blink while doing a task and they observed weaker FRN in this

condition as compared to the "blink-free" (participants could blink freely) condition. If we assume that blink free condition is less effortful than we can interpret the result as weaker FRN is duo to effort. However, one could argue that the change in FRN can arise from the unpleasantness (or the punishment) of the blink-free condition, not cognitive effort per se. In the experiment design of the second study, Gheza et al., (2018), participants first had gambled to obtain monetary reward, and if they lost, they exerted effort to gain the reward. That is the FRN of gain gamble condition is being compared with the loss gamble plus effort condition. That is, any changes in FRN from gain gamble condition to the loss gamble plus effort condition does reflect effort vs non effort condition and at the same time gain vs loss gamble condition. Thus, the decrease of FRN can be a response to the gamble loss rather than the cognitive effort.

The result of the current experiment offers a solution to the effort paradox: "effort is both costly and valued". In other words, the question is why sometimes we avoid and why sometimes we approach an effortful task. If we accept that cognitive effort is not inherently aversive, and that it is only arousing, then we can use Knutson et al., (2014) reasoning that people avoid situations with negative valence and high arousal and approach situations with positive valence and high arousal. This could suggest that it is the combination of high arousal of effort, on a one hand, and pleasantness or unpleasantness of the task, on the other hand, that determines whether doing the task is experienced as negatively or positively. Put more simply, we avoid effortful unpleasant tasks, but we approach effortful pleasant ones.

Continuing with the ERP analysis, we examined the P3 component in the context of the LC-P3 hypothesis, which posits that P3 reflects the phasic activity of noradrenergic neurons in the locus coeruleus (Aston-Jones and Cohen, 2005). So, we take P3 as a measure of arousal to test if it correlates with self-reported effort. The results show that P3 amplitude increases with task difficulty, providing further support for the arousal approach showing that the more effortful the task becomes the higher P3 increases. However, besides from the changes in the difficulty level, we didn't see a

correlation between the P3 amplitude and reported effort this is in line with Polish (2007), who argues that the early P3 — that appears around 300 ms — originates from stimulus-driven frontal attention mechanisms during task processing and thus it depends on task parameters.

The final result about the stimuli-locked ERP revealed distinct activity patterns associated with different cognitive strategies, even in the early components of the ERP that reflect sensory information processing of the stimuli (figure 13). The impact of cognitive strategies on the early component of the same stimuli in the ERP pattern has been previously reported (Fabiani et al., 1990). We interpret this as evidence that cognitive strategies can influence how stimuli are perceived.

Moreover, regarding the impact of cognitive strategies, while the importance of how people perform a task is often acknowledged (Shepherd, 2023; Dunlosky et al., 2020), this study is perhaps the first to empirically demonstrate the consequences of that variation for both effort and performance. Specifically, we observed that participants using the static strategy in the N-back task reported exerting less effort yet achieved higher scores than those using the rolling strategy (Figure 13). This pattern highlights a crucial insight: different strategies can modulate the cognitive demands of a task, meaning that performance alone is not a reliable indicator of the cognitive effort invested. A strategy that makes a task cognitively lighter can result in higher performance with lower subjective effort, thereby decoupling the usual assumption that higher performance implies higher effort. This challenges the common practice of using performance as a proxy for effort in economics without considering the underlying strategies employed.

The law of least effort could thus be reframed as a statement about cognitive strategy. In the simplest terms the law of least effort says: if there are several ways of doing something, given everything else being constant, the less effortful way is chosen (Hull, 1943). Thus, the law of least effort predicts that people choose static over rolling

cognitive strategy objectively, given everything else being constant. Future research could empirically test this hypothesis.

2-5-4 Performance

A key difference between the two approaches is their predictions about the relationship between cognitive effort and performance. While the valence approach predicted a positive correlation between reported effort and performance score within difficulty levels, the arousal approach predicted no relationship between reported effort and performance score within difficulty levels. The results favour the arousal approach, demonstrating that within each difficulty level and cognitive strategy, performance is independent of cognitive effort. This suggests that cognitive effort is not a deliberate choice variable that people can modulate; rather, once individuals commit to performing a task, they adhere to the prescribed steps of their cognitive strategy. To illustrate this concept, consider a worker whose role is to serve tea. The prescribed procedure involves boiling water at 100°C and adding a teabag Whether he is rewarded 1 or 10 euros, whether he is less or more motivated to exert less or more effort, that will not change the boiling point of water to 150°C or 50°C; the water always boils at the 100°C. That is to say, the task demand is not a matter of our choice.

In the N-back task, the average d-prime of the 3-back difficulty level in the rolling and static strategy was about 2.5 and 3 respectively. This is above the average of the literature, as the average d-prime of the 3-back difficulty level for the experiments with training is about 2 (Laine et. al., 2018). This suggests that during the training phase our participants were able to successfully learn the cognitive strategy and were able to be executed during the test phase of the experiment.

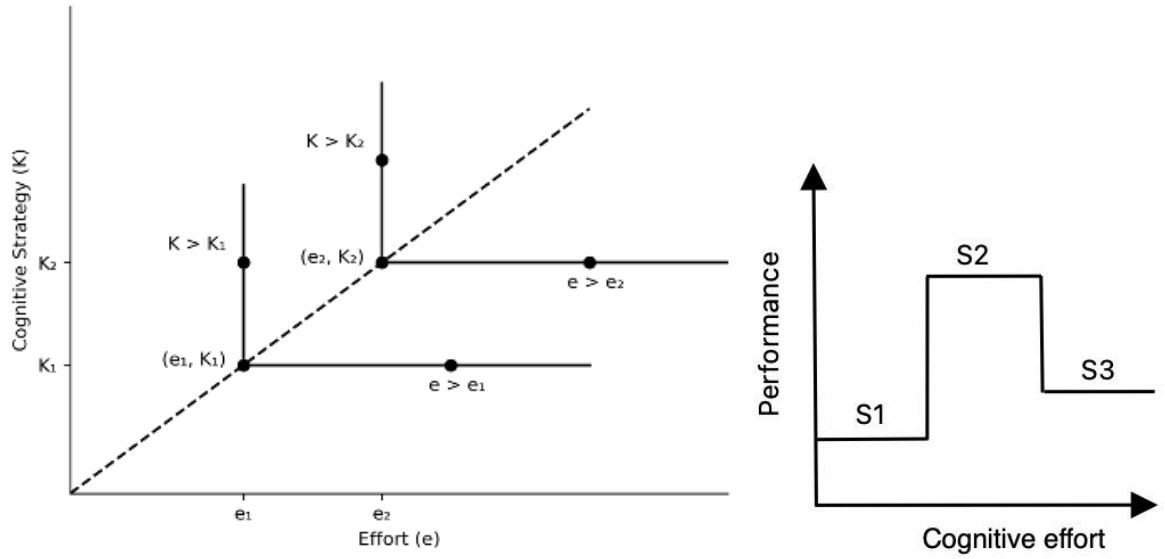

Figure 2-16: The left figure (panel A) presents to you a proposed production function of cognitive strategy and effort as input factors. The x-axis is cognitive effort and y-axis is cognitive strategy. The "L-shaped isoquants" represent all the combinations that yield same level of output. The performance increases only if both inputs increase. (i.e. moving from one isoquant to the other can only be by moving from (e_1, k_1) to (e_2, k_2). If either inputs stay constant changing the other ((e_1, k_2) or (e_2, k_1)) would not change the output (we stay on the same isoquant). This can explain why change in cognitive effort within difficuly level does not change the score. The right figure (panel B) presents to you the proposed relationship between cognitive effort and performance within a difficulty level. S1, S2, S3 are three different cognitive strategies (e.g., Rolling, Static). The characteristics of cognitive strategy maps domain of cognitive effort to codomain of performance.

Result also showed significant difference between the reported effort and performance score when comparing the rolling and static strategy in the N-back task. The static reported as less effortful while achieving higher performance score. We interpret this result as static being a "smarter" strategy than rolling. This result indicates that cognitive effort and cognitive strategy do not substitute one another but instead are complementary: excessive cognitive effort, when combined with an inadequate cognitive strategy, results in performance being constrained by the limitations of the strategy itself. This relationship between cognitive effort, cognitive strategy and performance might best be conceptualized by "perfect complement" production function (Leontief, 1951) as shown in figure 2-16 a.

Let us illustrate the production function with a hypothetical example. Assume one PhD student and one laptop can produces one scientific article per year. Two PhD student and one laptop would still produce one article per year because a student needs its instrument to write the article. Equally, one PhD student and two laptop would still produce one article per year because one student cannot simultaneously work on two laptops at the same time. Only with two PhD students and two laptops two articles per year can be produced. This example is an analogy of the relationship between cognitive effort and cognitive strategies. That is to say, that effort change can change score only if at the same cognitive strategy changes.

This would mean that the relationship between cognitive effort and performance within difficulty level is piecewise and non-monotonic (figure 2-16 b). Piece-wise because of the complementary relationship between cognitive effort and cognitive strategy. Non-monotonic because there can be cases such as static as compare the rolling that more performance can be achieved by less cognitive effort.

The Yerkes–Dodson law empirically demonstrates an inverse-U relationship between arousal and performance (Yerkes & Dodson, 1908). This means that low performance is associated with either too little or too much arousal, and that an optimum level of arousal in the middle maximises performance. How can we reconcile this inverse-U relationship with the non-monotonic, piecewise relationship between performance and cognitive effort that we claim here? There are two answers to this question. Firstly, we know that arousal resulting from cognitive effort differs from other types of arousal, such as stress (Sokolov, 1963; Sabat et al., 2025). Thus, the two relationships may concern two different phenomena and do not have to be similar; the two statements, one about the relationship between effort and performance and the other about the relationship between stress and performance, can both be true at the same time. The second answer is that the role of cognitive strategies in the inverse-U relationship is unclear. It could be that, after controlling for cognitive strategies, the inverse-U shape is also present in the relationship between cognitive effort and performance, as shown

in figure 2-16 b. Further research controlling for cognitive strategies when studying the relationship between (general) arousal and performance could clarify these possibilities.

2-5-5 Limitation

We want to emphasize that the task design should be considered when interpreting these findings. Participants operated under time constraints, with a one-second response window per trial. This limitation may have minimized opportunities for task disengagement or "mind wandering." If participants had more time, the relationship between effort and performance might shift toward a positive correlation, although the data show that reaction time increased with effort. In other words, in our experiment the pace was fixed, and it might be the case that the *pace* of exerting cognitive effort play an important role.

Furthermore, participants rated their effort before receiving performance feedback. If feedback had been provided earlier, it could have been used as a clue for the participant's and potentially influencing their self-reports, potentially reinforcing a positive relationship between self-reported effort and performance. These factors highlight the complexity of the effort-performance relationship and the importance of task design in shaping observed results. They also suggest avenues for future research to better understand these dynamics under varying task conditions.

2-6 Appendix

Why hit rate - false alarm rate as the scoring regime?

Based on signal detection theory, the subject's responses can be categorized into 4 categories: True positive, when the subject correctly presses the key, and it is correct. A false positive is when the subject wrongly presses the key. True negative is when the subject correctly doesn't press the key, and False negative is when the subject wrongly does not (Table 2-4).

Actual\Response	Positive	Negative
Positive	True positive	False negative
Negative	False positive	True negative

Table 2-4: 4 scenarios of response evaluation of the "signal detection theory" (Green, 1966).

The d-prime is defined as Z (Hit Rate) - Z (False Alarm Rate)

Where hit rate and false alarm rate are:

Hit rate = True Positives / (True Positives + False Negatives)

False alarm rate = False Positives / (True Positives + False Negatives)

and Z(x) is the Z-score is the inverse of the cumulative distribution function of the standard normal distribution. The score in the task is:

Score = number of Hits - number of False alarms

Maximization of the score would mean either increasing the number of hits or decreasing the number of false alarms, which would increase the hit rate and decrease

the false alarm rate, respectively. Finally, because the Z-function Z(x) is monotonically increasing, meaning that if a < b, then Z(a) < Z(b) Thus we can conclude that maximizing the score is the same as maximizing d-prime.

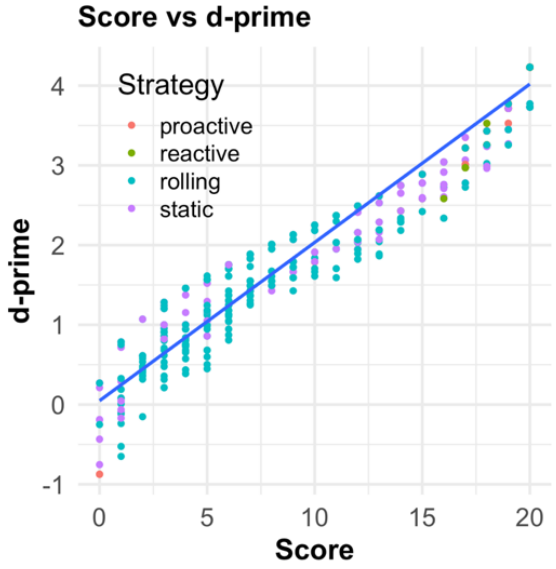

Figure 2-17: The strong correlation between d-prime and score is presented here for all the strategies. This is a confirmation that maximizing score means maximizing d-prime. Note that each score can corresponds to several d-prime because incorrect clicks on trials where the score was zero didn't decrease the score however, they impacted the d-prime as they were false alarms.

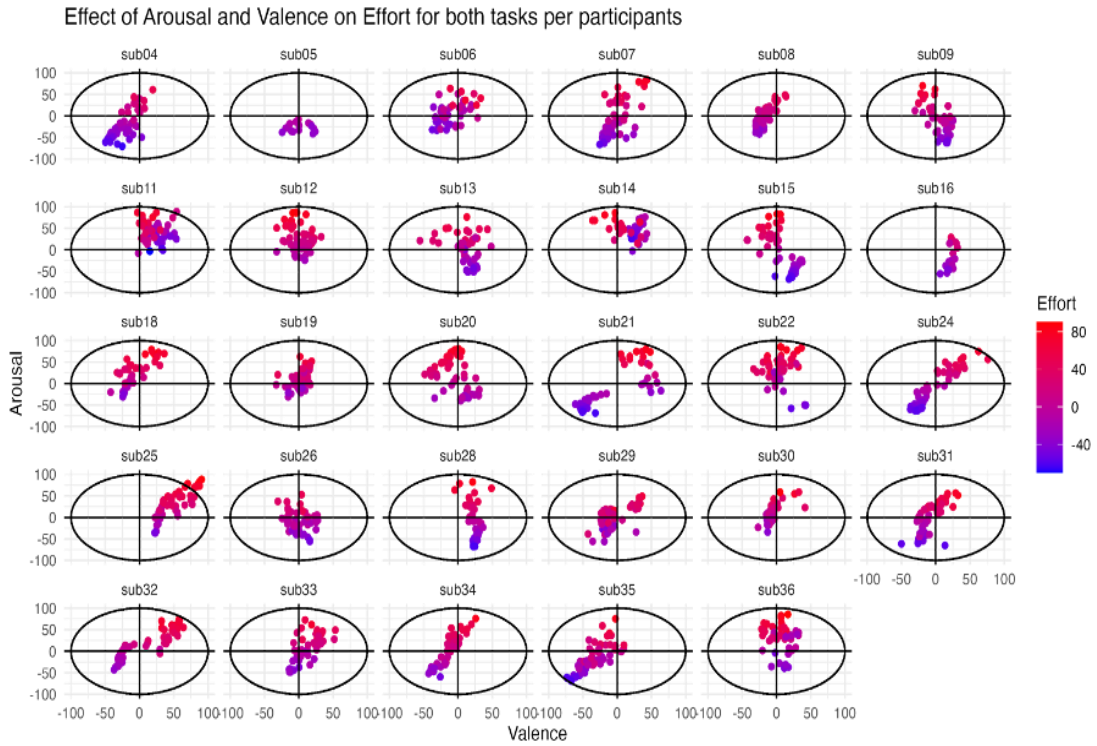

Figure 2-18: The position of self-reported valence and arousal by individuals for both tasks. You can see that the relationship between effort and valence is negative only for the participants 09, 14, 15, and 20.

Chapter 3

The preceding chapter reported empirical findings on the physiological, introspective, and behavioral manifestations of cognitive effort, and its relationship to task performance. These results provided initial evidence that cognitive effort is limited to cognitive strategy and some form of individual capacity. Building on this foundation, the current chapter aims to explore in greater depth the cognitive processes that underlie and constitute cognitive effort. We seek to unpack the mechanisms through which cognitive effort translates into behavioral performance. This analysis contributes to a more nuanced description about the mechanisms underlining cognitive effort.

In Pursuit of the Resource: Arousal contribution to Selective attention[p]

Abstract

While the exertion of cognitive effort is reliably accompanied by physiological arousal, the precise nature of the "resource" mobilised during such exertion remains unclear. The biological basis of this process is yet to be fully understood; however, this study focuses on the information processing aspect of the resource rather than its biological basis. Drawing on electrophysiological and oculomotor evidence, the study hypothesises that arousal enhances the intensity of selective attention by accelerating neural synchronisation, thereby increasing information throughput. Phase-amplitude coupling (PAC), the mechanism by which the phase of slower oscillations (e.g., theta) modulates the amplitude of faster ones (e.g., gamma), provides a neural marker of this synchronisation, reflecting how large-scale rhythm structure local information processing. Using a formal model based on the "binding-by-synchrony" hypothesis and empirical data from an N-back task combining electroencephalography (EEG), pupillometry and eye tracking, the study finds that arousal, indexed by pupil dilation, interacts positively with PAC (modulation index) to predict task performance (hit vs miss). These findings suggest that arousal facilitates the faster binding of relevant

[p] This chapter greatly benefited from the contributions of Tom Verguts.

features through enhanced neural synchronisation, shedding light on the computational basis of cognitive effort and resource mobilisation.

3-1 Introduction

There is much that remains unknown or the subject of debate when it comes to cognitive effort. However, research has consistently shown that cognitive effort is arousing. Time and time again we have seen that when people are engaged in cognitively demanding mental activity the physiological response shows heighten arousal; characterised by increased pupil dilation, cardiovascular reactivity, skin conductance, and electroencephalogram alpha desynchronisation (Van der Wel & Steenbergen, 2018; Fairclough & Houston, 2004; Gendolla et al., 2012; Hess & Ennis, 2011; Naccache et al., 2005; Venables & Fairclough, 2009).The heightened arousal during exertion of cognitive effort has led some authors to consider arousal as a key component in theorising about cognitive effort. We call their position the arousal approach in here.

The function of arousal is as it has been argued, to mobilize “mental resources” to meet task demands. However, the precise definition of the resource is still unclear, and it remains somewhat abstract (Pessiglione et al., 2025). In this paper, our primary aim is to investigate the resource as a means of processing, rather than as an entity of a biological nature.

The following is a concise summary of the arousal approach, first outlined in Kahneman (1973). This approach defines cognitive effort as "the intensity of selective attention" and delineates the role of arousal. Secondly, we briefly review the findings of more recent neuroimaging studies on selective attention and arousal. Thirdly, we update to the initial formulation of arousal approach based on these recent studies of selective attention. Finally, a hypothesis is put forward regarding the potential role of

arousal in intensifying selective attention, or cognitive effort. This hypothesis is tested using the chapter 2's dataset.

3-1-1 Capacity model of attention

When deciding to engage in an effortful mental task such as playing chess, answering emails, or reading, we restrict ourselves to a set of task-relevant stimuli associated with the ongoing activity. In other words, performing a mental task involves selectively attending to certain stimuli or aspects of stimulation while ignoring others. How this selection process occurs has been explained by the "bottleneck theories" (Broadbent, 1958; Deutsch & Deutsch, 1963). These theories argue that, at a certain stage of sensory processing, the simpler features of unattended stimuli (auditory or visual) are filtered out and do not proceed to higher stages of processing. Whether this filtering occurs before or after the grouping of these features into coherent precepts, known as "Gestalt grouping", has been a matter of debate. That is, the discussion has focused on whether this structural filtering occurs prior to or following Gestalt grouping.

As an alternative to these structural models, Kahneman (1973) proposed the "capacity model of attention," which emphasizes a general, limited capacity for mental work. Unlike bottleneck theories, this model does not posit a structural constraint but rather suggests that attentional capacity can be flexibly allocated, depending on one's intentions and the level of arousal. For example, imagine a taxi driver who is speaking at the same time with his passenger. When it comes to turn left, he excuses himself and allocate his attention away from the discussion to the road and when he made the turn he re-allocates back to his passenger. This example was given to illustrates that the limited capacity of attention can (at least partially) be flexibly oriented.

Beyond the selectivity of attention, the intensity with which we attend also influences our response. This intensity is subject to limitation. For example, a schoolboy sometimes can be distracted to something else than to his teacher. However, he might

also be less attentive to his teacher not because he is distracted to something else but because he is drowsy and simply has less capacity to give. In fact, Berlyne (1960) demonstrated that attentional intensity is linked to the level of arousal. Building on this, Kahneman argued that the amount of capacity allocated to mental work is modulated by arousal.

The relationship between limited capacity and arousal is well illustrated in Callaway's "dual-task paradigm" (1953, 1959, 1960), in which participants were instructed to perform two effortful tasks, designating one as primary and the other as secondary. When participants were given Amphetamine, which increases arousal, performance on the primary task improved at the expense of the secondary task. Conversely, when given Atropine, which decreases arousal, performance on the primary task declined while performance on the secondary task improved. According to the capacity model, increased arousal reduces the spare (or unallocated) capacity, thus impairing performance on the secondary task. Decreased arousal, on the other hand, increases spare capacity, allowing for better performance on the secondary task.

Although the evidence for a limited capacity is compelling, its precise nature remains unclear. Current knowledge offers only a few clues: first, that it is closely related to arousal; second, that it contributes to task performance or response accuracy; and third, that it influences the amount of sensory information transmitted through the bottleneck.

3-1-2 The neuroscience of selective attention

The study of selective attention is closely associated with the study of the visual system. This was primarily due to the fact that the direction of selective attention, ocular saccades, or fixation can be documented, whereas this is not feasible with the orienting response to auditory stimuli. As Mioche and Singer (1989) and the scientific report of Malsburg (1994) showed, the implantation of electrodes in the visual cortex of awake,

behaving kittens resulted in the demonstration of synchronous oscillatory activity, concurrent with the kitten's attention to a specific stimulus. The oscillatory frequency was found to be in the range of 40 Hz, which corresponds to the gamma frequency. The "binding-by-synchrony" hypothesis was developed as a result of this research. This hypothesis suggests that neurons that encode features (e.g., red and circle) of the same object (e.g., red circle) fire in a synchronized manner (i.e., their activity oscillates together) to bind them together and give rise to a unitary perceptual experience. This conjecture was based on the observation that synchronization appeared to conform to the same perceptual Gestalt grouping criteria previously mentioned (Gray and Singer, 1989; Gray et al., 1989).

Subsequent studies demonstrated that the synchronized oscillatory activity is not solely stimulus-driven; it also manifests in anticipation of "attention-demanding discrimination" tasks. In summary, the aforementioned activities have the potential to serve as correlates of intensifying attention (or focus), thereby contributing to the selection of stimuli (Roelfsema et al., 1997). Consequently, this research prompted a series of experiments, which established a positive correlation between arousal and the occurrence of gamma oscillations (Herculano-Houzel et al., 1999; Munk et al., 1996).

Concurrently, research on "binocular rivalry" has yielded direct evidence that synchronization is imperative for the bottlenecking of attention. In the binocular rivalry experiments, each eye is presented with a different image (e.g., A to the left eye and B to the right eye). The images cannot be fused into a coherent whole (e.g., superimposed A and B); instead, perception alternates between the two images (e.g., A or B) every few seconds. This phenomenon occurs because the images cannot be perceived as a fused whole, but rather as two distinct images that alternate in a regular pattern. The objective of these experiments is to facilitate the analysis of the two distinct bindings originating from the left and right eyes, respectively, with the ultimate aim of ascertaining the binding that successfully traverses the bottleneck. The result from such an experiment conducted in strabismus cats indicates that visual stimuli

that are consciously perceived (i.e., those that pass through the bottleneck) are associated with robust synchronization of the corresponding oscillatory responses in the primary visual cortex. In contrast, images that are suppressed and excluded from perception (i.e., filtered out by the bottleneck) result is associated with responses that are significantly less synchronized (Fries et al., 1997, 2001).

So far, we have described the hypothesis that the synchronized high frequency activity of neurons sensitive to different features of a visual stimulus is a mechanism for Gestalt binding. And that the bottleneck is associated to the change in the strength of this high frequency synchronized oscillatory activity. In such a way that more selected and relevant information have higher synchronization and those who are not selected and less relevant have less strength. The aforementioned explanations were provided in the context of selective attention; however, the issue of selective attention *intensity* remains unaddressed. The degree of intensity of selective attention can be understood through the examination of information processing speed; the more rapid the processing of information, the greater the associated intensity.

Research has demonstrated that a stimulus in the visual system is processed within approximately 120 to 150 milliseconds in order to reach perceptual consciousness (Kirchner and Thorpe, 2006; Thorpe et al., 1996). According to Fries (2023), allocating processing resources for more than the necessary time (i.e., 120–150 ms) on a single stimulus would be inefficient and wasteful. This approach would involve ignoring other stimuli, which is a suboptimal use of resources. Consequently, under conditions of attended stimulation, the frequency of these transitions would be approximately 7-8 times per second, corresponding to a theta rhythm. This suggests that the ocular movements should have the theta rhythm, which has been confirmed (Jutras et al., 2013). The location of attention is generally focused on the fovea of the eyes. Attention shifts are associated with saccadic shifts in fixated positioned of the eye with small shifts during fixation, known as “microsaccades” (Hafed and Clark, 2002). In the context of visual scene exploration, human subjects exhibit a theta rhythm (6-8 Hz) in

the distribution of saccadic together with the microsaccade ocular movements (Otero-Millan et al., 2008).

According to the findings of Holcombe and Chen (2013), in the event that one visual target the attentional sampling rate – the average amount of times that the participants looked at the moving target – has the high temporal resolution of 7 times per second (7 Hz). When a second moving target is introduced then the sampling rate each target reduced to 7 Hz divided by two. And when a third moving target appeared the sampling rate reduced to 7 Hz divided by three. This means that attention samples separate stimuli sequentially at the theta frequency, thereby expressing the limited resource.

3-1-3 Arousal contribution to binding

A substantial body of literature exists which documents the increase in theta power of the frontal EEG in response to cognitively demanding tasks (see Cavanagh & Franck, 2014), or those tasks that require intense selective attention. The "binding by random burst" hypothesis suggests a novel mechanism through which increased frontal theta may facilitate enhanced synchronization and strength of high-frequency gamma oscillations, thereby contributing to effective binding of features. This hypothesis was proposed by Verguts (2017). It has been demonstrated that this phenomenon can induce a coupling between the phase of the theta cycle and the amplitude of the gamma oscillation through a mechanism referred to as "noise-induced synchronization" (Zhou et al., 2005). Noise-induced synchronization is when several oscillators with different starting conditions move in synchrony when they receive common random input signals, even if they aren't connected.

As the result of receiving common even random input signals the difference between phase of the activity of the oscillators start converging to zero and the activity oscillators will have the same phase. This means that the oscillators become synchronize and we see a coupling between the amplitude of their activity and the

phase, known as phase-amplitude coupling. The degree of phase-amplitude coupling can be quantified by a method called modulation index (Canotly et al., 2006). The ensuing method section presents an argument for how arousal can increase the rate of convergence between phase of the oscillators, or potentiate the modulation index, and in this sense intensify the selective attention. There is some evidence for this hypothesis, Tomar et al., (2021) reported that arousal can enhance the phase amplitude coupling in CA1 subfield of Hippocampus.

The impact of arousal on neural activity is formulated in the "gain modulation" model (Aston-Jones and Cohen, 2005). The model delineates the modulating role of noradrenergic neurons in the locus coeruleus on the responses of their target cells, thereby augmenting the efficacy of synaptic transmission. Consequently, the sensitivity of a group of neurons to minute alterations in input stimuli is amplified, leading to heightened excitation or inhibition, contingent on the characteristics of the synapses. This modulation is related to selective attention through the descending influence of prefrontal regions on the locus coeruleus (Ghosh and Maunsell, 2024), which is distinct from the general notion of arousal.

It was mentioned before that the (visual) attentional sampling rate exhibits theta rhythmicity because processing stimuli takes 120–150 milliseconds (Fries, 2023). The method section also examines whether increased cognitive effort leads to increased process time and, consequently, a decrease in microsaccade rate (Hafed and Ignashchenkova, 2013). A review of the extant literature on microsaccades is provided by Martinez-Conde et al. (2013). Despite the necessity for further research to elucidate the relationship between cognitive effort and microsaccade rate (Dalmaso et al., 2017; Gao et al., 2015; Krejtz et al., 2018), Siegenthaler et al. (2013) demonstrated, through the implementation of straightforward and challenging arithmetic tasks, a negative relationship, indicating a reduced microsaccade rate when elevated cognitive effort is demanded. However, it is imperative to ascertain whether this phenomenon extends to other cognitive tasks.

The relationship between microsaccade rate and arousal remains a relatively understudied area of research. A significant challenge in the study of arousal pertains to the induction of this state, compounded by the heterogeneity of arousal manifestations. These include, but are not limited to, cognitive processes, stress responses, and sleep (Sabat et al., 2024). To the best of our knowledge, the majority of studies have reported no relationship between emotional arousal (e.g., stress, fear) and microsaccade rate (Yep et al., 2018; Krejtz et al., 2020; Chen et al., 2021; although see Kashihara et al., 2013). However, it is well documented that saliency (which induces arousal) leads to an increase in the microsaccade rate referred to as "microsaccade enhancement" (Wang et al., 2020). Nonetheless, irrespective of the nature of the relationship between arousal and microsaccade rate - whether it is negative or positive - the combination of pupil size and microsaccade rate would be an effective method for measuring cognitive effort. Specifically, pupil dilation accompanied by a decrease in microsaccade rate would be a physiological response to effort, whereas pupil dilation accompanied by no change in microsaccade rate would be a response to other forms of arousal.

In summary, the Gestalt grouping mechanism is believed to take place by means of bursts of high gamma frequency oscillatory activity at a rate of 7 times per second, leading to attentional sampling in the theta rhythm. This comprehensive mechanism signifies the existence of a coupling between the phase of low-frequency theta and the amplitude of high-frequency gamma. The objective of this study is to verify the hypothesis that arousal, as indexed by pupil size (Joshi et al., 2016), enhances coupling, as indexed by the EEG frontal modulation index, and decreases attentional sampling, as indexed by microsaccade rate. The present study examines this hypothesis by analysing the available dataset of chapter 2.

3-2 Methods

3-2-1 Formal analysis

3-2-1-1 Gain model

The assumption of the gain model is that arousal increases gain, the parameter $g > 0$ in the transfer function of equation 1 (Servan-Schreiber et al., 1990) which controls the steepness of the sigmoid function that transfer net input signal $I(t)$ to output signal $r(t)$:

$$r(t) = \frac{1}{1 + exp\,(-g(I(t) - B))} \qquad 3\text{-}1$$

$I(t) = s(t) + \xi(t)$ is the total input signal to the ensemble of neurons, decomposed into a deterministic signal $s(t)$ and a stochastic noise term (t). With B being the firing threshold. By substituting the input decomposition into the function, we yield:

$$r(t) = \frac{1}{1 + exp\,(-g(s(t) + \xi(t) - B))} = \frac{1}{1 + exp\,(-g(s(t) - B) + g\xi(t))} \qquad 3\text{-}2$$

Equation 2 shows that arousal by increasing the gain parameter scales both the signal (s(t)) and the noise ($\xi(t)$). This means that gain increases the effect of signal and noise that will be useful for the equation 3.

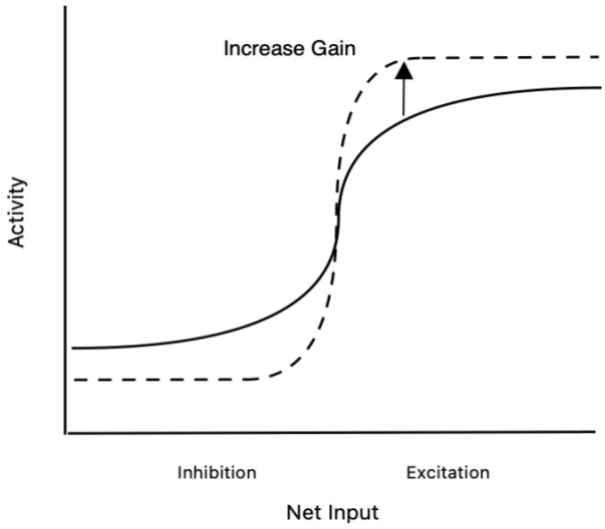

Figure 3-1: Gain model of arousal, the activation or transfer function defines the relationship between a unit's net input and its activity state, such as the firing rate of a single neuron or the mean firing rate of a population (assembly of neurons), as described by equation 1. An increase in gain amplifies the activity of units receiving excitatory input (upward arrow on the right) and suppresses the activity of units receiving inhibitory input (downward arrow on the left), enhancing the contrast between excited and inhibited units (Servan-Schreiber et al., 1990).

To quantify the impact of gain on synchronization we turn to two oscillators using the formulation provided in Goldobin and Pikovsky (2005). And we examine their phase difference. If their phase difference converges to zero, it means that they will synchronize and if it doesn't converge to zero then it means that they will not synchronize.

3-2-1-2 Oscillators

Consider two uncoupled ensembles of neurons that receive noise input from common source (common (t)). Each oscillator's position on its cycle can be described by a phase variable $(t) \in [0,2\pi)$. The evolution of their respective phases, $\theta_i(t)$ and $\theta_2(t)$, can be described by:

$$\frac{d\theta_i}{dt} = \omega + g \cdot \sigma \cdot Z(\theta_i) \cdot \xi(t), \qquad i = 1,2 \tag{3-3}$$

Where ω is the intrinsic frequency, $Z(\theta_i)$, is the the effect of input on the oscillator's phase which has σ as baseline. $Z(\theta_i)$ characterizes how input at a given phase θ_i shifts the timing of the next spike (Ermentrout & Kopell, 1990; Winfree, 2001). The phase difference $\phi = \theta_1 - \theta_2$:

$$\frac{d\phi}{dt} = g \cdot \sigma[Z(\theta_1) - Z(\theta_2)] \cdot (t) \tag{3-4}$$

Because $\phi = \theta_1 - \theta_2$ is a small number we can Taylor estimate $Z(\theta_1)$ by θ_2. That is to say $Z(\theta_1) = Z(\theta_2 + \phi) \approx Z(\theta_2) + Z'(\theta_2) \cdot \phi$. So, the linearized phase difference equation becomes:

$$\frac{d\phi}{dt} \approx g \cdot \sigma Z'(\theta_2)\phi \cdot \xi(t) \tag{3-5}$$

3-2-1-3 Synchronization of the oscillators

The sign of "Lyapunov exponent" (negative vs positive sign), λ describes stochastic exponential growth (desynchronization), or stochastic exponential decay to zero (synchronization) (Arnold, 1998; Gardiner, 2009).

$$\lambda = \lim_{t\to\infty} \frac{1}{t} ln \left|\frac{\phi(t)}{\phi(0)}\right| = \lim_{t\to\infty} \frac{1}{t} \int_0^t g \cdot \sigma Z'(\theta_2)\phi \cdot \xi(t) \quad 3\text{-}6$$

By the stochastic calculus (Teramae & Tanaka, 2004; Goldobin & Pikovsky, 2005), the Lyapunov exponent (rate of separation) for this type of equation can be computed as:

$$\lambda = -\frac{1}{2} g^2 \cdot \sigma^2 \cdot E[Z'(\theta_2)^2] \quad 3\text{-}7$$

Equation 6 shows $\lambda < 0$, means negative rate of separation implying convergence of phase and synchronization of the two oscillators. Crucially, the exponent decreases quadratically with gain, leading to faster convergence or synchronization under higher gain.

3-2-2 Task

The dataset is based on the N-back task (Kirchner, 1958), in which participants are presented with a continuous stream of letters and instructed to respond whenever the current letter matches the one shown N positions earlier. Task difficulty increases with larger values of N (e.g., 1-back, 2-back, 3-back), requiring greater cognitive effort. Each trial lasts 2 seconds: a letter is displayed for 1 second, followed by a 1-second inter-stimulus interval. Each block contains 60 trials, with a total of 22 blocks. The experiment includes two cognitive strategy conditions—rolling and static—which determine how participants engage with the task.

3-2-3 Data recording

3-2-3-1 Electroencephalogram (EEG)

EEG was recorded continuously with an Active-Two Biosemi system, using 64 channels (with five external electrodes, two on mastoids, two temples, and one below the left eye) with a sample rate of 512 Hz. The electrodes' offset values were checked prior to recording and kept under 25mV. The system was synchronized to the stimulation computer through a parallel port. Yet to ensure precise timing between the triggers and stimuli displayed on the monitor, two photocell sensors, placed on the extreme right and left sides of the monitor, masked from the subject vision, were flashed simultaneously to each letter stimulus.

3-2-3-2 Eye Tracker

We used an Eyelink 1000 plus desktop-mount infrared-video based eye tracker to record the eye position and pupil diameter from the right eye, with a sampling rate of 500Hz.

3-2-4 Data analysis

3-2-4-1 Pupil size

We used the Eyelink parsing algorithm to identify blinks in the time series. We removed periods starting 200 ms and ending 200 ms after each blink. Further for each recording, we identified outlier time points as those pupil diameters that were beyond three standard deviations from the participant's average, and we removed these time

points from the analysis. Last the pupil diameter of every recording is scaled to the range between 0 to 1 using the equation: $x' = \frac{x - \min(x)}{\max(x) - \min(x)}$, where x is the pupil diameter, to normalize values across participants. From this, we computed for each 2-second target trial the averaged pupil diameter.

3-2-4-2 Microsaccade rate

To analyse microsaccade we followed recommendations from (Engbert and Kliegl, 2003). We first identified periods of fixation based on the Eyelink algorithm. In these periods we computed the smoothed instantaneous velocity, v(t) using the following equations:

$$v_x(t) = \frac{\vec{x}_{t+2} + \vec{x}_{t+1} - \vec{x}_{t-1} - \vec{x}_{t-2}}{6\Delta t}, v_y(t) = \frac{\vec{y}_{t+2} + \vec{y}_{t+1} - \vec{y}_{t-1} - \vec{y}_{t-2}}{6\Delta t} \quad 3\text{-}8$$

Where $v_x(t)$ and $v_y(t)$ represent the horizontal and vertical velocity of the eyes at time t, respectively. We assumed a minimal microsaccade duration of 6 ms (three data samples at 500 Hz). Next to protect the analysis from noise, the thresholds for the $x_t y_t \Delta t$ detection algorithm were based on the median of the velocity time series as follows:

$$\sigma_x = \sqrt{\langle v_x^2 \rangle - \langle v_x \rangle^2}, \sigma_y = \sqrt{\langle v_y^2 \rangle - \langle v_y \rangle^2} \quad 3\text{-}9$$

The $\langle\rangle$ sign denotes the median estimator. Finally, the necessary condition for a microsaccade is to fulfil the criteria:

$$\frac{v_x}{\lambda\,\sigma_x} + \frac{v_y}{\lambda\,\sigma_y} > 1 \qquad 3\text{-}10$$

λ is the threshold multiplier. As λ increases, the number of detected microsaccade decreases (that are labelled by 0 or 1 for each time point). In this study we chose $\lambda = 6$, following guidelines from the literature (Engbert and Kliegl, 2003). We verified the linear relationship between peak velocity and amplitude.

To analyse the temporal dynamics of microsaccade occurrence, we computed a time course of microsaccade rate across trials. Each recording block consisted of 60 trials, each lasting 2 seconds. Data were sampled at 500 Hz, yielding 1000 time points per trial. For each time point, we assigned a binary label to indicate the presence or absence of a microsaccade: 1 indicates microsaccade present, 0 indicates no microsaccade and NaN indicates a blink or a large saccades (i.e. periods outside fixations).

Next, we computed the average number of microsaccade during the 2-second trials to have the microsaccade rate (number/second). And finally, the model below was used to statistically see the impact of difficulty level (D_{ij}) and its interaction with the two condition (cognitive strategies) (S_j: Rolling or Static) on microsaccade rate (M_{ij}) for each block i. We also included random intercept for participants ($u_{\mathrm{sub}[j]}$) to control for subjective variability.

$$M_{ij} = \beta_0 + \beta_1 D_{ij} \times S_j + u_{\mathrm{sub}[j]} + \epsilon_{ij} \qquad 3\text{-}11$$

3-2-5 EEG data

3-2-5-1 Preprocessing

Pre-processing was carried out using Brainstorm (Tadel et al., 2011) using scripting mode to ensure replicability and provide reusable material. For each participant, the power spectrum density was estimated to control for the overall quality of the recording and to identify bad channels. After bad channel rejection, the continuous data was inspected to identify segments of data containing artifacts (e.g. muscle activity, movements, except eye blinks). Signals were offline re-referenced to the average of the mastoid. Continuous data was then band-pass filtered between 0.25 and 95 Hz, and a 50 Hz notch filter was applied. After marking the bad segments, 32 components of Picard Independent Component Analysis (ICA) on the continuous recording applied to remove artifacts from blinks and eye movements.

3-2-5-2 Modulation index

In the N-back task, the trials that the participant is supposed to make a click response, those that are the same as N trials back, are called “targets”. To study the phase amplitude coupling we looked at the target trials and compare the correct response (hit) vs incorrect response (miss) to the target trials (Busch et al., 2009; Bahramisharif et al., 2018). We quantify the phase amplitude coupling of these trials using the “modulation index” (MI) method of Canolty et al. (2006), known as “mean vector length”.

To have a reliable result from this method it is highly encouraged to use a signal which length is at least ten cycles of the slowest oscillation in the low oscillation band. Because the trial length is 2 seconds, meaning that the slowest oscillation we could have access

to is 5 Hz. So, we decide the slow frequency range to be [5,13] and we decided the high frequency range to be [30,95].

Next, we observed the coupling map between every phase of the low frequency (5 - 13) to the amplitude of every high frequencies (30 - 95) so that we arrive to 520 number of MI for each low phase and high amplitude frequency combination for every trial. These maps are known as "comodulogram" (appendix page 178). The colour of the image indicates the level of coupling between each pair of low and high frequencies. By examining the comodulogram of the target trials, we realized that the variation is as much that at the end by averaging them we will end up with black noise and we will lose all the specificity. To avoid this, for each trial's comodulogram we chose the maximum MI across all 520 pairs as the MI of that trial and then we averaged the absence of response to targets together (miss trials) and correct response to targets together (hit trials) separately.

Finally, to examine the impact of modulation index of the trial i (MI_{ij}) through its interaction with pupil size (P_{ij}) on performance (F_{ij} : Hit 1, or Miss, 0) the binomial logistic model that is presented below is executed. In addition, the interaction of difficulty level (D_{ij}) with cognitive strategy (S_j : Rolling or Static), the block number (B_{ij}), and random intercept ($u_{\mathrm{sub}[j]}$) for each participant j are included as co-variate in the model.

$$F_{ij} = \beta_1 MI_{ij} \times P_{ij} + \beta_2 D_{ij} \times S_j + \beta_3 B_{ij} + u_{\mathrm{sub}[j]} + \epsilon_{ij} \qquad 3\text{-}12$$

3-3 Results

3-3-1 Modulation index

The results of the mixed model logistic regression (Table 3-1) revealed that interaction between modulation index and pupil size is a significant positive predictor of performance ($\beta = 3.015$, SE = 1.455, z = 2.07, p = .038). Block number was also found to have significant positive coefficient on with performance ($\beta = 0.044$, SE = 0.003, z = 14.06, p < .001). In terms of task difficulty, the interaction between difficulty and the rolling condition showed a strong negative effect ($\beta = -1.678$, SE = 0.047, z = -35.92, p < .001), indicating that increased difficulty substantially reduced the likelihood of a correct response in the rolling condition. A similar but smaller negative interaction was found in the static cognitive strategies ($\beta = -0.697$, SE = 0.056, z = -12.40, p < .001). These findings reflects that task difficulty impaired performance across conditions, as expected (figure 3-3).

	Estimate	Std. Error	P-value
MI x Pupil	3.014765	1.455466	0.0383
Block number	0.043882	0.003122	<2e-16
Difficulty x Rolling	-1.678196	0.046716	<2e-16
Difficulty x Static	-0.696835	0.056215	<2e-16

Table 3-1: This table reports regression results with coefficients ("Estimate"), standard errors, and p-values for each predictor. Significant effects include interactions between modulation index and pupil size (*MI x Pupil*), task difficulty (1-back, 2-back, 3-back) with dynamic and static stimuli (*Difficulty x Rolling*, *Difficulty x Static*), and a strong effect of task progression (*Block number*). P-values indicate all predictors are statistically significant.

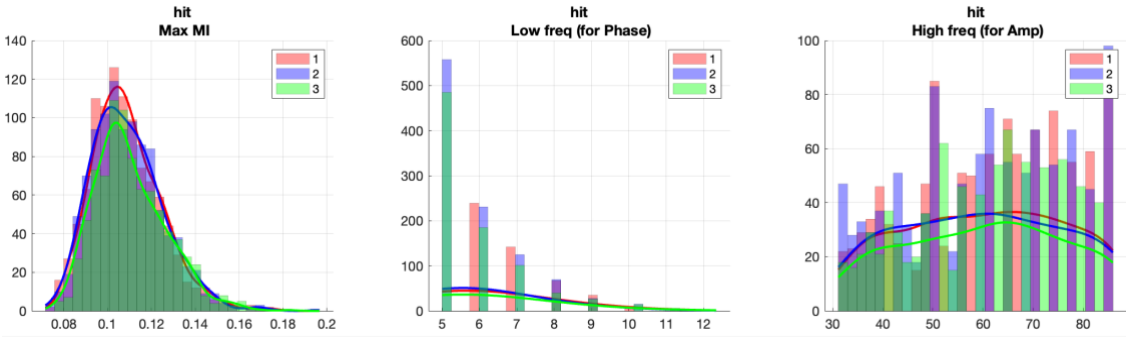

Figure 3-2: Distribution of the Modulation Index (MI) features for hit trials across difficulty levels in the rolling cognitive strategy (for the static cognitive strategy see the appendix page 178). The left column shows the distribution of Max MI values; the middle and right columns show the corresponding low-frequency (phase) and high-frequency (amplitude) coordinates at which the Max MI occurs. While the Max MI distributions are smooth and consistent across conditions, the distributions of the corresponding frequency coordinates are highly variable and non-specific. This lack of specificity in low and high frequency localization suggests that averaging based on frequency coordinates may be misleading. Therefore, analyses should focus on the Max MI values themselves, rather than their coordinates.

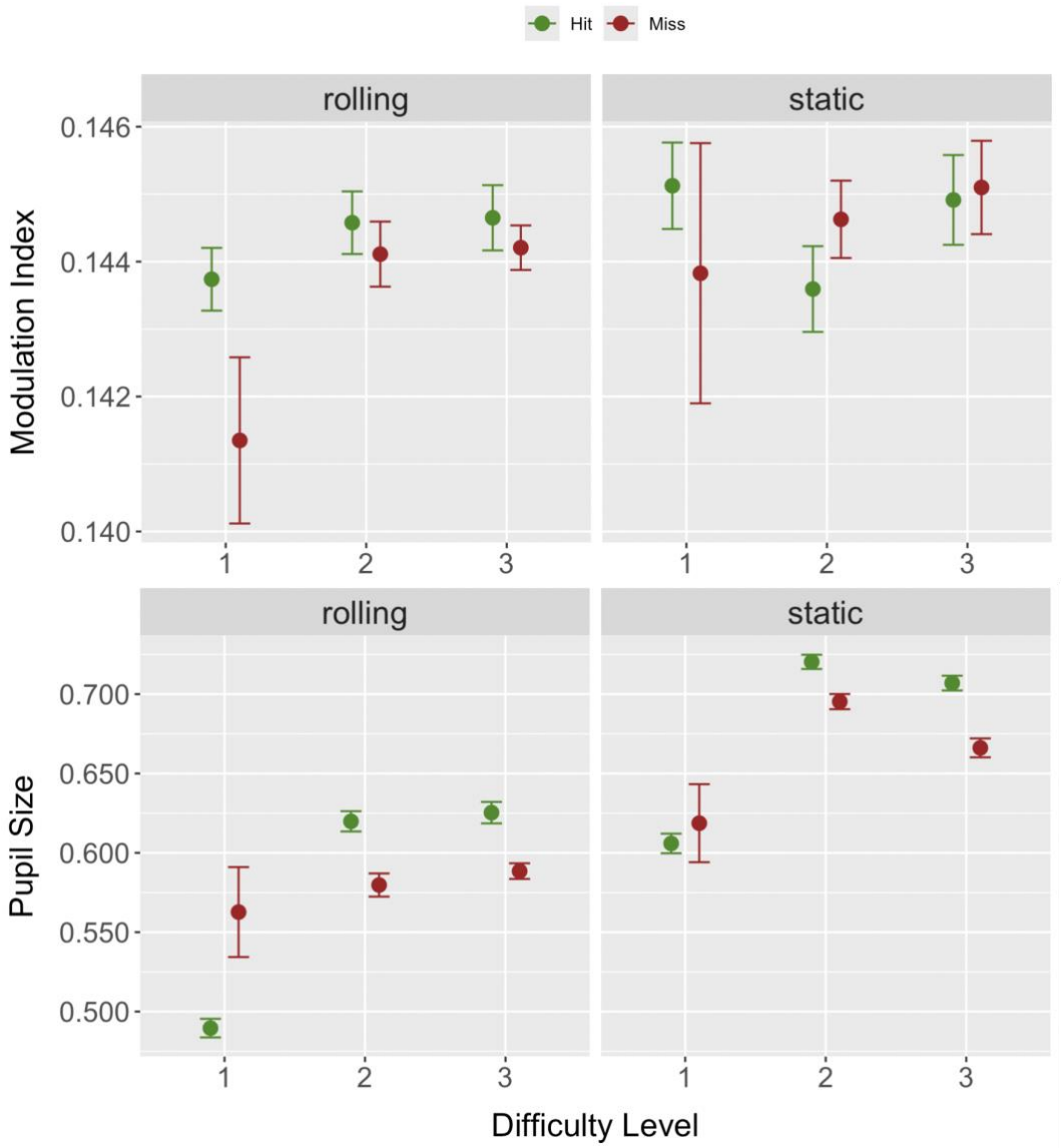

Figure 3-3: The bottom panel shows changes in pupil size across difficulty levels in the rolling and static cognitive strategies of the N-back task, separately for hit and miss trials. Pupil size increases with difficulty in both trial types; however, within each difficulty level, it is consistently greater for hits than for miss. The top panel presents the Modulation Index (MI) with a similar pattern: MI for hit and miss trials increases with difficulty (non-monotonously in the static). Within each difficulty level, MI is smaller for miss than for hit trials, mirroring the pupil size trend and leading to the positive significant interaction effect on performance shown in Table 3-1.

3-3-2 Microsaccade rate

A linear mixed-effects model was used to examine the interaction between task difficulty and cognitive strategies (Rolling and Static) on the microsaccade rate (Table 3-2), while accounting for random effects. The analysis revealed a significant negative interaction between difficulty and the rolling cognitive strategy (β = -0.065, SE = 0.026, t (3992) = -2.50, p = .0126), indicating that as task difficulty increased, microsaccade rate decreases in the rolling cognitive strategy, which is according to the initial hypothesis. In contrast however, there was a significant positive interaction between difficulty and the static cognitive strategy (β = 0.174, SE = 0.035, t (3864) = 4.99, p < .001), suggesting that increased difficulty was associated with higher microsaccade rate which is contrary to our hypothesis. These results suggest that maybe the changes in microsaccade rate when engaging in an effortful mental activity can depend on the specific cognitive strategy that the participants is adopting.

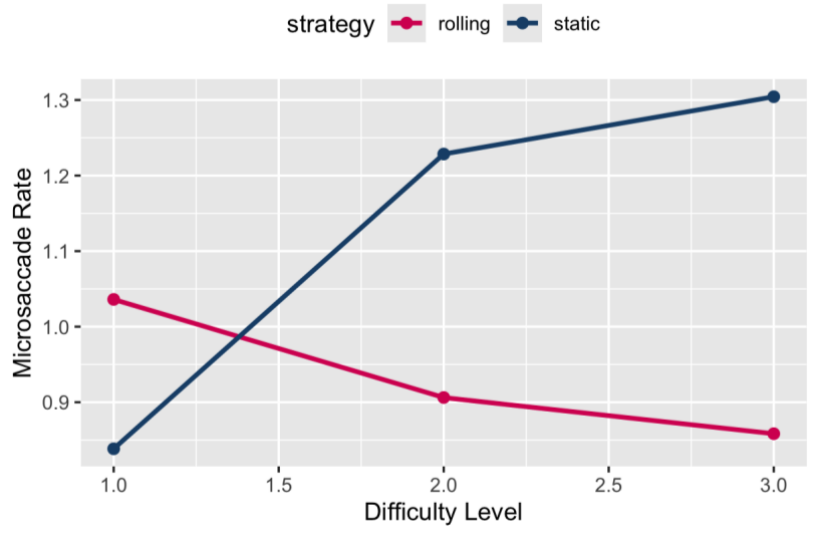

Figure 3-4: This figure illustrates the interaction between task difficulty (1-back, 2-back, 3-back) and cognitive strategy (rolling vs. static) on the microsaccade rate. Microsaccade rate decreases under the rolling strategy (as expected). In contrast, microsaccade rate increases under the static strategy (contrary to our hypothesis). This result highlights the complexity between microsaccade rate and cognitive effort and that it might be modulated by the cognitive strategy.

	Estimate	Std. Error	P-value
Difficulty x Rolling	-0.06499	0.02604	0.0126
Difficulty x Static	0.17386	0.03485	6.35e-07

Table 3-2: This table shows regression coefficients ("Estimates") for the interaction between task difficulty (1-back, 2-back, 3-back) and cognitive strategy. The negative estimate for *Difficulty x Rolling* suggests that increasing difficulty reduces the outcome under rolling conditions, while the positive estimate for *Difficulty x Static* indicates the opposite effect under static conditions. Both effects are statistically significant.

3-4 Discussion

It is an established fact that exertion of cognitive effort – that is to say, the intensity of selective attention – is associated with heightened arousal. Whilst it is generally accepted that the role of arousal is to mobilise resources, the precise nature of these resources remains unclear. In this article, we restrict our focus to the information processing aspect of the resource, while acknowledging that its biological basis remains to be explored in future research.

According to the binding-by-synchronisation hypothesis, the neurons that encode the features of the selected stimuli are synchronised, whereas the neurons that encode the unselected or ignored stimuli are not synchronised. By synchronization it is meant that the difference in the phase of the activity of these ensemble of neurons becomes zero. This indicates that their activity exhibits the same phase (in the theta frequency). We saw in equation 6 that arousal by increasing the gain modulation decreases the Lyapunov exponent (rate of separation which when it is negative it's the rate of convergence). The rate of convergence can by interpreted as the intensity of selective attention or cognitive effort. The faster the convergence or the faster the synchronisation, the more stimuli or information can be processed within a given time frame.

The increase in the speed of synchronisation can be interpreted as an increase in the resources allocated to the selected stimuli. A formal analysis indicates that an increase in arousal (i.e. gain modulation) can theoretically accelerate the process of synchronization. The hypothesis is tested using an N-back task, with the pupil size and modulation index (MI) of mid-frontal electrodes (Fz, F3, F4) being measured for hit and miss trials. The result confirmed the hypothesis by showing the positive interaction of pupil size and modulation index, which was correlated positively with the probability of the trial being a hit rather than a miss. As the difficulty level increases, so does the size of the pupils. However, it was observed that the pupils in the hit trials were larger than those in the miss trials. The same is true for the MI; it increases with higher difficulty levels, and the MI for hit trials was higher than the MI for miss trials (see Figure 3-3).

We also test the "phase reset" hypothesis of microsaccade rate. The concept under discussion is that a binding occurs within a microsaccade. Therefore, a delay in microsaccade processing corresponds to a decrease in microsaccade rate, indicating that more information is processed. The result was puzzling; in the rolling cognitive strategy, the microsaccade rate of hit trials correlated negatively with difficulty level as expected. However, the microsaccade rate of hit trials correlated positively with difficulty level, contrary to our initial expectations. These results underscore the intricate dynamics between microsaccade rate and the intensity of selective attention. Further research is needed to determine the component that can determine the direction of changes in microsaccade rate when engaging in more cognitively effortful difficulty levels.

Further investigation is required to determine the generalisability of these results, which relate to the relationship between pupil size and MI. It is also necessary to ascertain whether these results are merely correlational or causational. But if we assume that the indeed pupil size — the index of the activity of noradrenergic neurons of Locus Coeruleus — leads to higher MI, then we can argue that maybe what is meant

by resource mobilization is speed of synchronization from the information processing perspective.

This study contributes to the existing body of literature that illustrates the importance of MI on performance. This effect has been studied in intracranial data and magnetoencephalography (MEG), but here we report the same result in the electroencephalogram (EEG): Tomar et al., 2021; Jones and Wilson, 2005; Köster et al., 2018; Bahramisharif et al., 2018. The fact that MI is associated with better performance – presumably through arousal or resource mobilisation – raises an important question: why aren't we always mobilising resources to operate at full capacity? Research findings on specific disorders may offer some solutions. For instance, MI is elevated in individuals with psychosis and autism (Sacks et al., 2021). In cases of psychosis, patients may experience delusions, which are defined as "fixed incorrect beliefs" and hallucinations – having sensory perception in the absence of a stimulus (Lee et al., 2019; Arciniegas, 2015). In the context of autism, the heightened sensitivity to sensory input exhibited by autistic individuals has been associated with elevated levels of MI (Sun, 2024).

The findings indicate that the process of synchronisation can result in the triggering of false alarms, i.e. instances where synchronisation is not required. Our results do in fact provide some indication of this idea (appendix page 178). The MI of false alarms trials is higher than that of hit trials, while the latter decrease and the former increases with difficulty level. This suggests that the relationship between resource mobilisation and performance may not be as monotonous as typically assumed. In other words, there can be optimum point of sufficient resource mobilisation as too much of it can be harmful (false alarm) and too little insufficient (miss).

We believe that further research into the relationship between modulation index, interaction arousal and performance (miss, hit, false alarm) could be a fruitful avenue.

3-5 Appendix

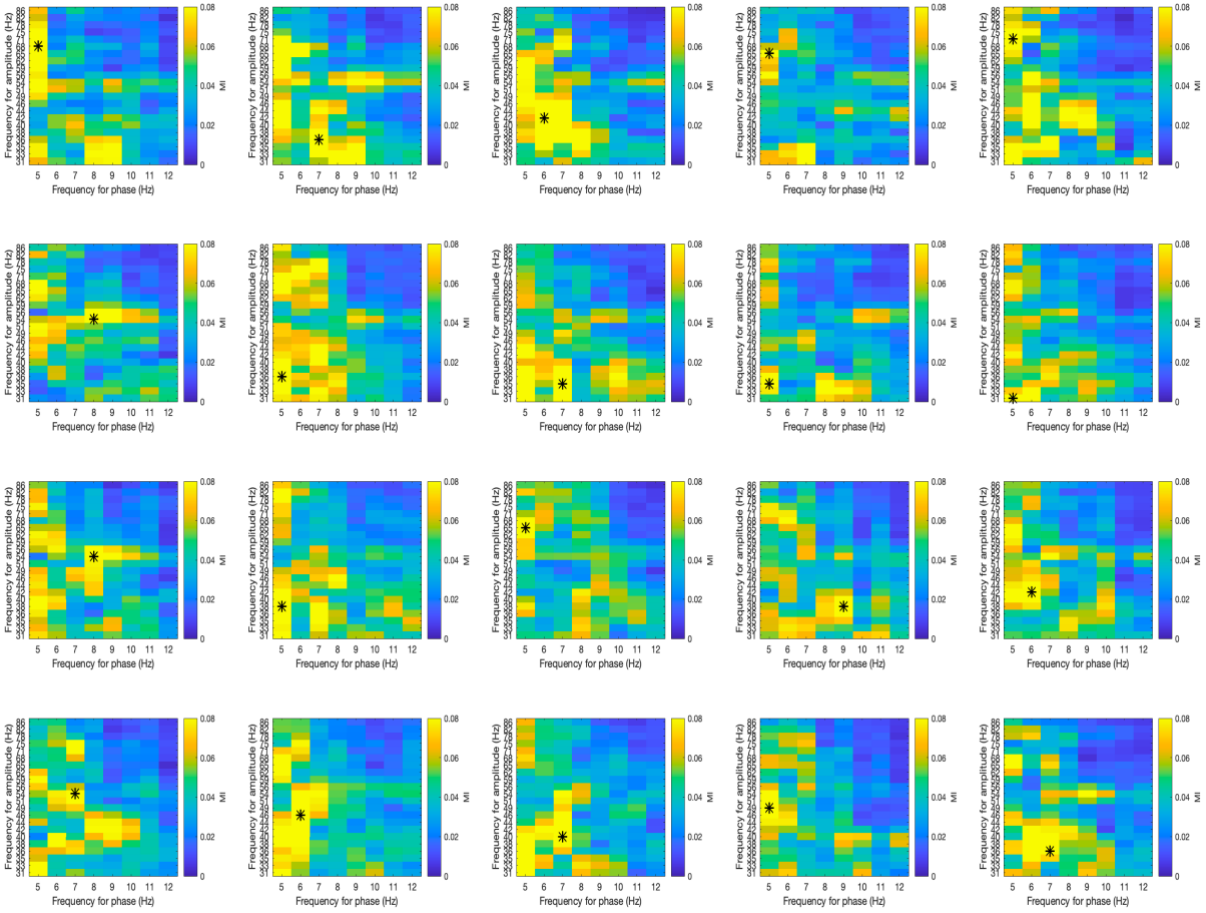

Figure 3-5: Here we are presenting to you the comodulogram of 20 trials. Each comodulogram is an image of the high frequency amplitude (y-axis) and low frequency phase (x-axis) coordinates of Modulation Index, MI (the colour). The star indicates the maximum MI. This example is meant to illustrate the degree of specificity which is lost after averaging the comodulogram by the x and y coordinates (as it is illustrated by the histogram of figure 3-6). This is why we decided to average by the maximum MI only.

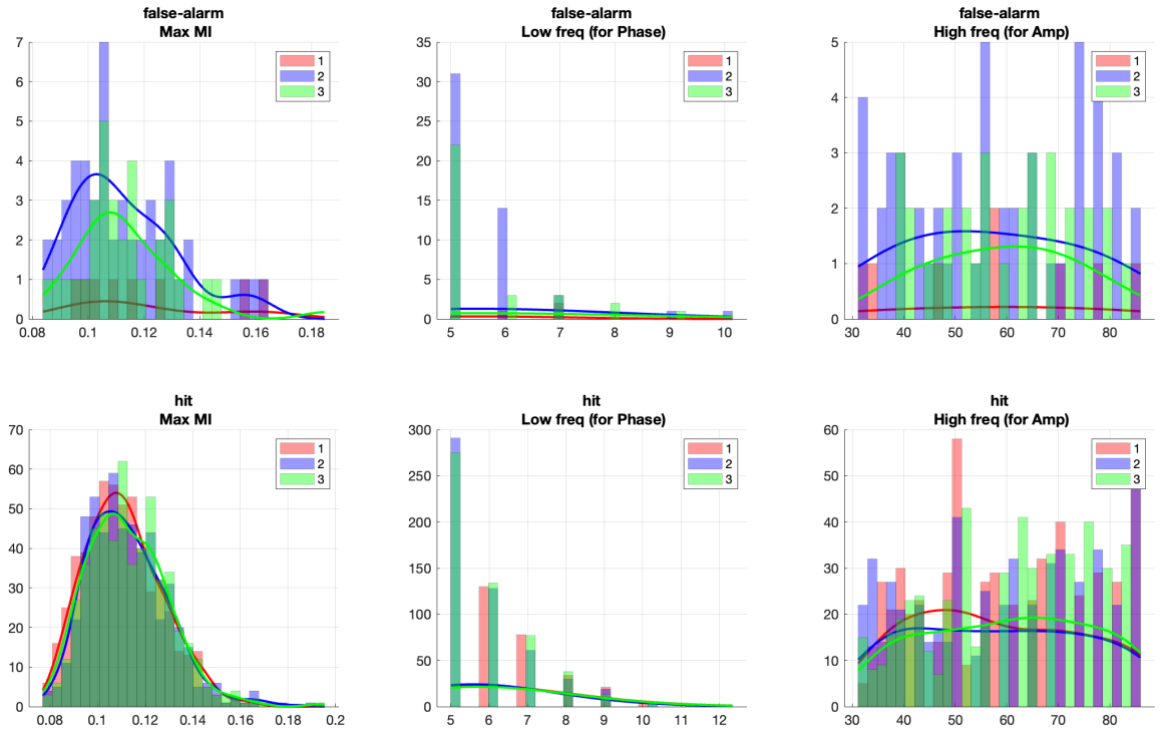

Figure 3-6: Distribution of the Modulation Index (MI) features for hit and false-alarm trials across difficulty levels in the static cognitive strategy. The left column shows the distribution of Max MI values; the middle and right columns show the corresponding low-frequency (phase) and high-frequency (amplitude) coordinates at which the Max MI occurs. While the Max MI distributions are smooth and consistent across conditions, the distributions of the corresponding frequency coordinates are highly variable and non-specific. This lack of specificity in low and high frequency localization suggests that averaging based on frequency coordinates may be misleading. Therefore, analyses should focus on the Max MI values themselves, rather than their coordinates.

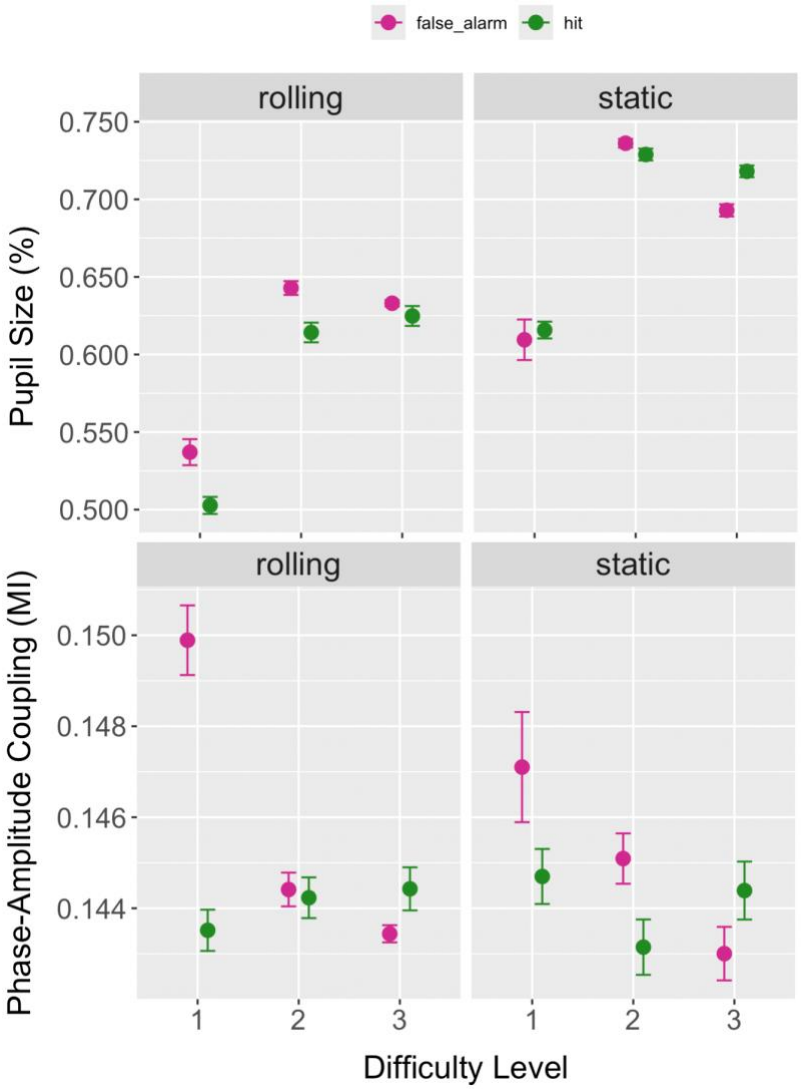

Figure 3-7: The top panel shows changes in pupil size across difficulty levels in the rolling and static cognitive strategies of the N-back task, separately for hit and false alarm trials. Pupil size increases with difficulty in both trial types; however, within each difficulty level, it is consistently smaller for hits than for false alarms. The bottom panel presents the Modulation Index (MI) with a similar pattern: MI for hit trials increases with difficulty (non-monotonously in the static condition), while MI for false alarm trials decreases. Within each difficulty level, MI is higher for false alarms than for hits, mirroring the pupil size trend.

General Discussion

In the preceding chapters, we explored cognitive effort through the lens of neuroeconomics. Chapter 1 introduced the key theoretical approaches, highlighting their conceptual foundations and differences. Chapter 2 tested the predictions derived from these frameworks through an experimental study using behavioural, physiological, and introspective measures. Chapter 3 then shifted focus to the cognitive mechanisms underlying effortful performance, emphasising the role of strategies and their interaction with arousal.

This general discussion brings together the insights gained across these chapters. By integrating the theoretical, empirical, and mechanisms, we aim to clarify the nature of cognitive effort and its relevance for economics and cognitive neurosciences. The discussion also identifies limitations, suggests directions for future research, and outlines the broader implications of our findings for understanding how effort is experienced, measured, and valued.

Cognitive Effort Reconsidered: Cognitive Strategies, Arousal, and Synchronization

According to labour supply theory, labourers will exert the minimum necessary effort irrespective of wage because wages are fixed and do not increase with increased effort. However, real-life observations show that higher wages are accompanied by greater effort. Gift exchange theory has attempted to improve upon these predictions in real-effort experiments, arguing that an increased wage can be perceived as a gift, which workers will reciprocate by exerting more effort. However, real-effort experiments do not offer a clear definition or consensus measure of effort (Charness et al., 2018). To address this issue, we turned to cognitive neuroscience, where we found that prominent neuroscience studies rely on labour supply theory to study cognitive effort (Kool & Botvinick, 2014). This led us to formulate the valence model (Botvinick & Braver, 2015), which we will review here. We also identified an older theory that has been largely overlooked: the arousal approach, which has neither been explicitly accepted nor rejected in the neuroeconomics literature. To address this gap, we designed an experiment to compare the two models and test their behavioural and physiological predictions. As summarised below, the findings provide strong empirical support for the arousal model.

Before the experiment began, the participants underwent training in specific cognitive strategies to guide their performance monitoring and selection processes systematically. The impact of these strategies was greater than we had initially anticipated: stimulus-locked ERPs for the task showed clear and reliable differentiation based on the learned strategy, as if the participants were responding to entirely different stimuli. This differentiation was not limited to EEG; it was also

reflected in almost all behavioural and pupillometry measures. The extent of these effects, along with their detailed implications, is reported below.

1 Phenomenology of cognitive effort

When participants were given the opportunity to rate their experience of effort (self-reported effort), they described it as active and not negative (self-reported valence). They also described it as active rather than passive (self-reported arousal). This perception was supported by physiological markers of arousal, including increased pupil dilation and a higher amplitude of P3b. Perceiving effort as neutral, rather than negative, was confirmed by feedback-related negativity (FRN), a physiological response to monetary gains and losses. Like self-reported valence, FRN was correlated to performance, but not to effort itself.

This result casts doubt on the cost hypothesis of cognitive effort. Further supporting this idea, participants continued to collect points even after meeting the minimum required to pass a block (e.g. 4, 8 or 12 points). If effort were inherently costly, why did they persist in exerting effort beyond what was necessary? This finding addresses the so-called effort paradox — the observation that effort is sometimes valued and sometimes perceived as costly — by suggesting that effort itself is neither intrinsically valuable nor costly. However, if this is the case, what then explains the undeniable aversiveness of certain effortful tasks?

Our results suggest two possible explanations that could be investigated further. Firstly, we observed a correlation between self-reported valence and FRN and performance. This suggests that part of the aversion to effort may stem from perceived efficacy: in other words, if we believe we are not good at something, we tend to avoid it. Secondly, we found that both self-reported valence and FRN were influenced by cognitive strategies, particularly in the N-back task, where both were higher for the

static strategy than for the rolling strategy. This indicates that strategies affect not only performance, but also the subjective perception of effort, potentially rendering a task more or less enjoyable. For example, consider someone who avoids swimming, believing that they dislike it. However, they later realise that they actually enjoy breaststroke but dislike the front crawl. Similarly, different cognitive strategies may influence whether an effortful task is perceived as aversive or engaging by altering the way it is experienced. And it also points to the imprecision on what is called a “task”.

2 From cognitive effort to performance

Within each difficulty level of the task, we found no correlation between reported effort and performance, which is consistent with the predictions of the arousal model but contrary to those of the valence model. However, we observed that, when accompanied by the static strategy, higher effort led to better performance than the rolling strategy. This suggests that cognitive effort and cognitive strategies may be complementary in determining performance: excessive cognitive effort combined with an inadequate strategy results in performance being constrained by the strategy's limitations.

It is also important to note that participants were under fixed time pressure. Had the experiment been self-paced, allowing participants to control their response speed, a positive relationship between effort and performance within each difficulty level might have emerged. The interplay between cognitive effort and cognitive strategy, and the role of time and response speed in shaping the effort–performance relationship, are intriguing questions for future research.

3 Definition of cognitive effort

According to the arousal approach, effort is defined as the intensity of selective attention. In this approach, the role of arousal was envisaged as increasing the capacity allocated to task demands. However, it was unclear what this capacity was, particularly given that brain energy consumption is almost always constant, and how arousal could increase it. To address this issue, we drew on existing theories of arousal and selective attention.

Arousal is a heterogeneous concept involving cognition, stress and sleep (Sabat et al., 2024), with different sources causing arousal, such as acetylcholine. Here, however, we have restricted ourselves to noradrenaline (NA) (Sara and Bouret, 2012) and the GAIN model (Aston-Jones and Cohen, 2005). We used pupil size as an index (Joshi et al., 2016; see also Megemont et al., 2016). Through formal analysis and experimental evidence, we demonstrated that NA enhances coupling between the amplitude of high-frequency gamma oscillations and the phase of lower-frequency theta oscillations.

A descriptive definition of cognitive effort (Gupta and Mackereth, 2023) can be derived from the aforementioned observation and the other main findings of the thesis, such as the positive correlation between self-reported effort and arousal and the modulatory role of cognitive strategies. Thus, cognitive effort may best be described as the experience of arousal when executing a cognitive strategy. The underlying mechanism is likely to be increased noradrenaline, which enhances phase amplitude coupling. One advantage of this definition of cognitive effort is that it can be tested and, if necessary, refuted or modified in future research.

One limitation of this definition is that it is confined to the execution of cognitive strategies, and it is unclear whether these strategies are also present in innovative work. In the N-back task, we saw that the static strategy was 'smarter' than the rolling strategy. The question is: how was this strategy discovered? Was this a separate,

effortful process? Previous studies on training and the N-back task may provide insight here (Ritakallio et al., 2024). Laine et al. (2018) demonstrated that participants taught the static strategy within a few training sessions achieved the same level of performance as those who underwent several weeks of ordinary N-back working memory training (Soveri et al., 2017). Malinovitch et al. (2018) also showed that successful learners of the N-back task — those who manage to improve their working memory capacity — discover the static strategy.

It would be interesting to study what determines an initial strategy, such as rolling, and how a more sophisticated strategy, such as static, is discovered naturally. It would also be interesting to find out if this discovery process itself requires cognitive effort. During development, cognitive strategies can have a profound impact on performance and engagement in effortful tasks. For example, we could study the strategies employed by more successful students compared to their classmates. It would also be interesting to investigate whether there are strategies that make studying more engaging.

4 Quantification of cognitive effort

Economists mostly use performance as a proxy to measure effort (Charness et al, 2018). However, as we showed the relationship between performance and effort is not at all self-evident and many other factors (such as chance) can influence performance. Sometime in economics, response time (RT) is used as a measure of effort (Ariely et al., 2009). However, the increased delay might be an indication of the confidence level not the amount of effort per se (Ratcliff et. al., 2009). Also, RT might be different by the design of the experiment whether it is self-paced, or the participants are under time pressure like in our case.

The valence approach most systematically measures cognitive effort as a trade-off between money and effort in the 'cognitive effort discounting' paradigm (see Chapter

2). For example, if the experimenter pays 2 euros for 3-back compared to 1-back, then the cost of effort is 2 euros. This type of trade takes place every day in labour markets and is a central topic in labour economics (Cahuc et al., 2014). However, this cannot be considered a measure of effort, because the initial motivation for measuring effort — at least from an economic point of view — is to determine the relationship between changes in effort and changes in performance or production, as well as how effort is traded — its price. However, the factors that determine the price of effort — and performance, as discussed previously — extend beyond effort alone (e.g. gift exchange, bargaining power).

As mentioned in the introduction, Jevons' quid pro quo assumption about the rational agent — known as the 'hedonic theory of wages' — that the pleasure of a reward must equal the pain endured to obtain it, lacks justification. Empirical work has failed to demonstrate this, with some studies even reporting that the most 'difficult' jobs have the lowest wages (Brown, 1980). Furthermore, when a job becomes more difficult, wages do not increase by more than those of the control population (DeSimone and Schumacher, 2004).

By contrast, the arousal approach usually employs pupil dilation and other arousal-related indicators to gauge effort. However, these measures are frequently criticised for being non-specific, as they can also reflect other types of arousal, such as stress. Here, we propose using microsaccade rate as a specific measure of cognitive effort. Existing literature suggests that microsaccade rate is independent of other forms of arousal, including stress, and aligns with the definition of effort, as it may play a key role in phase amplitude coupling and selective attention. Future research should investigate its specificity further by examining the conditions under which the rate changes and in which direction, as well as its generalisability across different effortful tasks. In particular, it should be established whether the rate consistently decreases with cognitive effort, especially because microsaccade seem to reflect that the relation between cognitive effort and cognitive strategy.

5 Limitations and future research directions

This thesis challenges two fundamental assumptions in standard economic models concerning cognitive effort. Firstly, the common presumption that effort is inherently unpleasant is critically re-evaluated. We argue that it is not effort itself that is costly, but rather the context in which it is exerted, such as the characteristics of the task or adverse working conditions, that contributes to its perceived unpleasantness. Secondly, we question the assumption that increased effort necessarily improves performance. Instead, we demonstrate that the relationship between effort and performance is not linear but rather depends on the deployment of effective cognitive strategies. These insights necessitate a more nuanced framework in which effort is not viewed as a inherent cost, but as a process influenced by subjective experience of the employed cognitive strategy.

One limitation of the current study is the way the difficulty levels were designed. In the N-back task, differences in strategy became most pronounced at the 3-back level. It would have been valuable to observe whether this difference converged or diverged as the difficulty level increased. In the AX-CPT task, the correlation between 'n' and 'c' favoured the proactive strategy heavily (see Table 3, Chapter 3). The post-interviews revealed that this sometimes-caused participants to use the proactive strategy, even when instructed to use the reactive strategy at the first difficulty level, when the correlation between 'n' and 'c' was 1. For example, when asked in the post-interviews what errors they had made, some participants said that they had failed to inhibit clicking in the absence of 'c' after seeing 'n', which is an error of the proactive strategy, whereas the reactive strategy is immune to this. They were supposed to use the reactive strategy, but this type of error suggests that they were using the proactive strategy. To address this, the correlation between 'n' and 'c' should have been designed to be more balanced, e.g. around 0.7, 0.5 and 0.3 rather than 1, 0.9 and 0.8. Future research

studying cognitive strategies should consider these adjustments, such as comparing rolling and static strategies at the 4-back level and comparing proactive and reactive strategies when the correlation between 'n' and 'c' is more evenly distributed.

A second limitation of this study is that we did not examine cognitive effort in the context of the labour market, so we do not know how it is traded. Specifically, the relationship between the amount of cognitive effort exerted and its price remains unclear. It is possible that, regardless of the amount of cognitive effort involved in completing a task, workers aim to sell their effort at the highest possible price. From this perspective, the price and amount of cognitive effort could be completely independent of each other.

From the perspective of labour demand, effort is an inherent cost because firms must pay wages to incentivise it. Similarly, from the perspective of labour supply, effort is also a cost. When wages are fixed, labourers may be reluctant to exert more effort, as any extra effort means producing rewards that could have been theirs, but which are owned by others, thereby incurring a cost. Future research could explore whether our findings on cognitive effort apply to a labour market context. For example, in a labour market where effort is a 'cost', is valence still independent of effort? Is there a correlation between effort and the price of effort, or, in other words, is there a correlation between the measure of effort (i.e. microsaccade rate) and the price of labour? How do changes in cognitive strategies that alter the productivity of labour through the relationship between cognitive effort and performance, as well as the pleasantness of labour through the relationship between cognitive effort and valence, impact pricing?

A third limitation of this thesis is that we did not explore the cognitive effort involved in making a choice. When individuals are faced with several alternatives, the amount of effort they invest in making the choice influences the final decision. Deliberate decisions tend to require more cognitive effort than impulsive ones. This concept also applies to selling effort — specifically, the effort involved in pricing. Could it be, for

example, that choices traditionally known as intuitive or effortless occur when phase amplitude coupling or microsaccade rates are high, while deliberate or effortful decisions occur when these rates are low? Future research could compare phase amplitude coupling and microsaccade rates for deliberate versus impulsive choices, in order to gain a better understanding of the cognitive effort involved in decision-making with regard to risk, time and altruism.

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Appendix

This appendix provides the complete set of protocol documents associated with the experimental procedure described in Chapter 2. These materials were essential to ensuring the consistency, reliability, and reproducibility of the experiment. They include:

General Instructions: This document outlines the initial written instructions that were provided to participants prior to the start of the experimental task. It explains the objective of the task, the structure of the experiment, and the rules governing participants' engagement. The instructions were designed to minimize ambiguity and ensure that all participants received uniform guidance.

Comprehension Assessment: Following the training phase, participants were required to complete an assessment designed to evaluate their understanding of the cognitive strategy they had been taught. This measure served both as a manipulation check and as a quality control step to confirm that participants had adequately internalized the training material before proceeding to the main task.

Post-Interview Questions: After the experimental task was completed, participants were invited to participate in a semi-structured interview. The document included here contains the set of questions used during these interviews. The aim of the post-interview was to gain qualitative insights into participants' experiences, their perceived use of the trained strategy, and any subjective factors that may have influenced their performance.

Training Correction Script: During the training phase, the experimenter used a standardized script to provide corrective feedback whenever participants made errors in applying the cognitive strategy. This document ensured that feedback was delivered

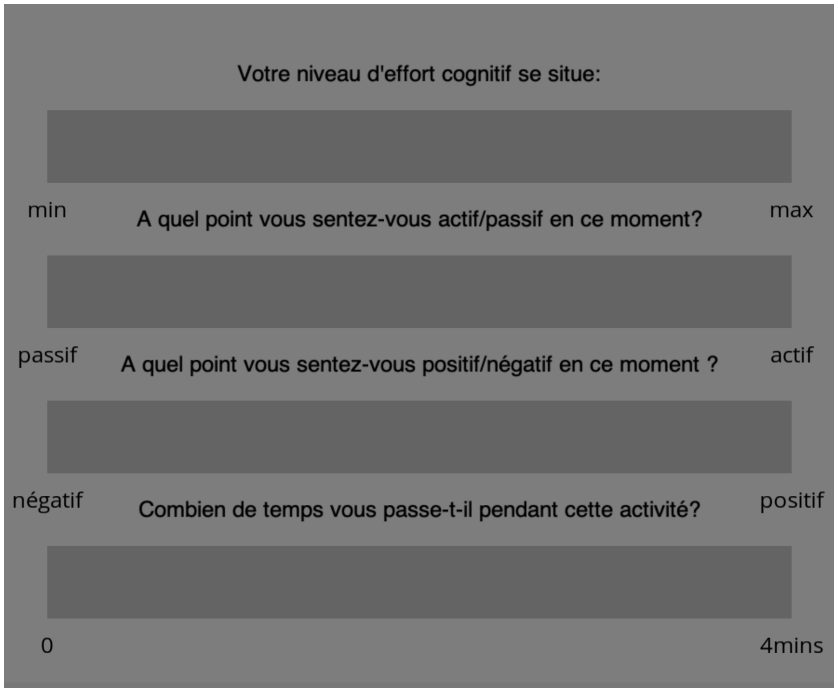
in a consistent manner across all sessions and participants, reducing experimenter-induced variability.

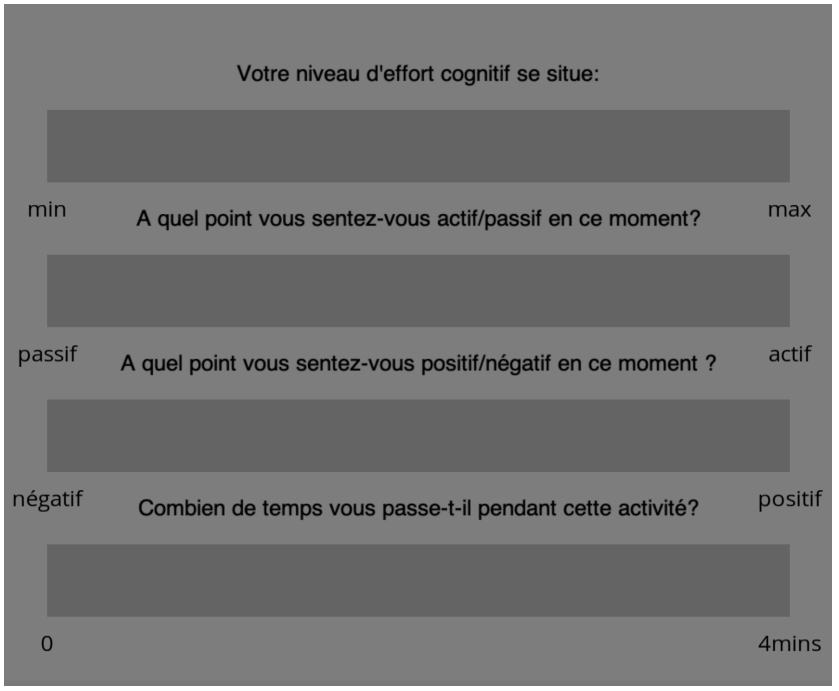
Together, these documents form a comprehensive overview of the procedural and instructional framework of the experiment. Including them here serves to enhance the transparency and reproducibility of the research.

Instructions générales

Veuillez éteindre vos téléphones portables dès maintenant et ranger vos livres, journaux et ordinateurs pendant toute la durée de l'expérience.	Please turn off your cell phones now and put away your books, newspapers, and computers for the duration of the experience.
Nous vous demandons d'être très attentif lors de la lecture des instructions. Elles doivent vous permettre de bien comprendre l'expérience.	We ask you to pay very good attention when reading the instructions. They must allow you to understand the experience fully.
Toutes vos décisions seront traitées de manière anonyme. Nous ne pourrons en aucun cas vous associer vos réponses.	All your decisions will be treated anonymously. We will not be able, under any circumstances, to link your answers to you.
L'expérience à laquelle vous participez a pour but d'étudier l'effort cognitif. Nous vous soumettrons à une tâche mentale avec différents niveaux de difficulté afin que vous puissiez nous rapporter votre expérience. Votre expérience nous intéresse.	The experiment in which you will participate is intended to study cognitive effort. To do so, we ask you to do an online task that has various difficulty levels. Throughout the experiment, we will ask you to evaluate your experience. Your experience is what we are interested in and we therefore ask you to tell us about it as truthfully as possible.
La tâche est effectuée sur un ordinateur et implique plusieurs essais. Cela commence par une séance de formation, au cours de laquelle nous vous guidons et vous expliquons la bonne façon de procéder. À ce stade, il est important de se concentrer sur la manière dont vous accomplissez la tâche, même si cela implique de commettre davantage d'erreurs.	The task is done on a computer. It starts with a training session, where we guide you through the task and tell you how to solve it. You may be making mistakes at the beginning but this learning phase will help you to get better at solving the task. The important thing is that you pay attention to the solution strategy we propose..
À l'étape suivante, vous devrez accomplir la tâche "pour de vrai". En d'autres termes, vous devrez atteindre un certain	At the next stage, you will have to do the task "for real". That is, you will have to achieve a certain predetermined goal of

objectif prédéterminé de nombre de réponses correctes. Si vous n'atteignez pas l'objectif prédéterminé, vous devrez répéter la tâche jusqu'à ce que vous réussissiez. Le score maximum que vous pouvez atteindre est de 20. Si vous cliquez et qu'il s'agit d'une erreur, vous perdrez un point. Le but est de comprendre vos efforts et votre expérience dans l'accomplissement d'une tâche. La répéter n'aura aucune conséquence, si ce n'est que vous apprendrez à mieux la faire et, par conséquent, à la réussir. Une fois que vous avez fini un bloc d'essais d'un un certain niveau de difficulté, nous vous poserons des questions à l'écran sur l'effort que vous avez fourni. Sur une échelle allant de l'effort minimum à l'effort maximum, vous devez nous dire quel effort vous avez fourni. Nous aimerions également savoir comment vous vous êtes senti pendant la tâche sur deux échelles différentes, l'une allant du négatif au positif et l'autre du passif à l'actif. Enfin, vous devez savoir que chaque bloc dure 2 minutes, mais nous aimerions que vous nous indiquiez le temps qu'il vous a semblé s'écouler entre le début et la fin; 2 minutes ou plus ou moins. Vous trouverez ci-dessous une capture d'écran des questions que vous devrez remplir après chaque bloc.	correct answer. In case you fail to achieve the predetermined goal, you have to repeat the task until you succeed. The maximum score that you can achieve is 20 and if you click and it was a mistak you will lose a point. The point is to understand your effort and experience in doing a task. Repeating it will have no consequences other than the fact that you will learn to do it better and, therefore, succeed. Once you have completed a level of difficulty of the task, we ask you some questions on the screen about your effort experience. On a scale from minimum to maximum effortfulness, you should tell us how much effort you invested. We would also like to know how you felt during the task on two different scales, one going from negative to positive and one from passive to active. Lastly, you should know that each block takes 2 minutes, but we would like you to indicate how much time it felt to you to complete; 2 minutes or more or less. Below you see a screenshot of these questions that you will have to fill in after each difficulty level.


Votre niveau d'effort cognitif se situe:
min
max
A quel point vous sentez-vous actif/passif en ce moment?
passif
actif
A quel point vous sentez-vous positif/négatif en ce moment ?
négatif
positif
Combien de temps vous passe-t-il pendant cette activité?
0
4mins


Votre niveau d'effort cognitif se situe:
min
max
A quel point vous sentez-vous actif/passif en ce moment?
passif
actif
A quel point vous sentez-vous positif/négatif en ce moment ?
négatif
positif
Combien de temps vous passe-t-il pendant cette activité?
0
4mins

N back (Rolling)

Dans cette tâche, une série de lettres "u", "c", "n", "m" et "s" est présentée à l'écran.



L'objectif global de la tâche est d'appuyer sur le clic gauche de la souris lorsque vous voyez une lettre que vous avez déjà vue. Si vous cliquez correctement, vous gagnerez un point. Si vous cliquez de manière incorrecte parce que la lettre vue précédemment n'était pas la même que celle qui apparaît actuellement à l'écran, vous perdrez un point. Vous devrez obtenir un nombre minimum de points corrects pour chaque niveau de difficulté de la tâche.

Il existe trois niveaux de difficulté. Dans la tâche la plus simple, vous devez cliquer lorsque vous voyez à l'écran la même lettre que celle que vous avez vue juste une lettre auparavant. Dans la tâche de niveau moyen, vous devez cliquer lorsque vous voyez la même lettre que 2 lettres auparavant. La tâche la plus difficile est celle où vous devez cliquer lorsque vous voyez la même lettre que 3 lettres auparavant (tâche la plus difficile). Nous expliquons

Pour vous rappeler le niveau de difficulté dans lequel vous vous trouvez actuellement, vous verrez dans le coin supérieur gauche de l'écran soit A,A (tâche la plus simple pour 1 lettre avant), A,B,A (tâche moyenne pour 2 lettres

In this task, a series of letters "u", "c", "n", "m", and "s" are presented on the screen.



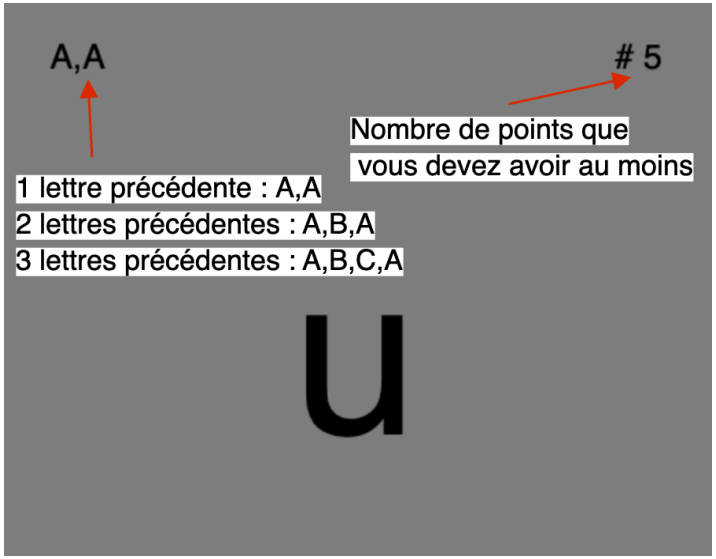
The overall aim of the task is to press the left-hand click of the mouse when you see a letter you have previously seen. If you click correctly, you will earn a point. If you click incorrectly because the previously seen letter was not the same as currently on the screen, you will lose a point. You will have to achieve a minimum number of correct points at each task's difficulty level.

There are three difficulty levels. In the simplest task, you must click when you see the same letter on the screen that you have seen just 1 letter before. In the medium-level task, you must click when you see the same letter as 2 letters before. The hardest task is the one where you have to click when you see the same letter as 3 letters before (hardest task). We will explain

To remind you of the difficulty level that you are currently in, you will see in the left top corner of the screen either A,A (simplest task for 1 letter before), A,B,A (medium task for 2 letters before) or A,B,C,A (hardest task for 3 letters before)

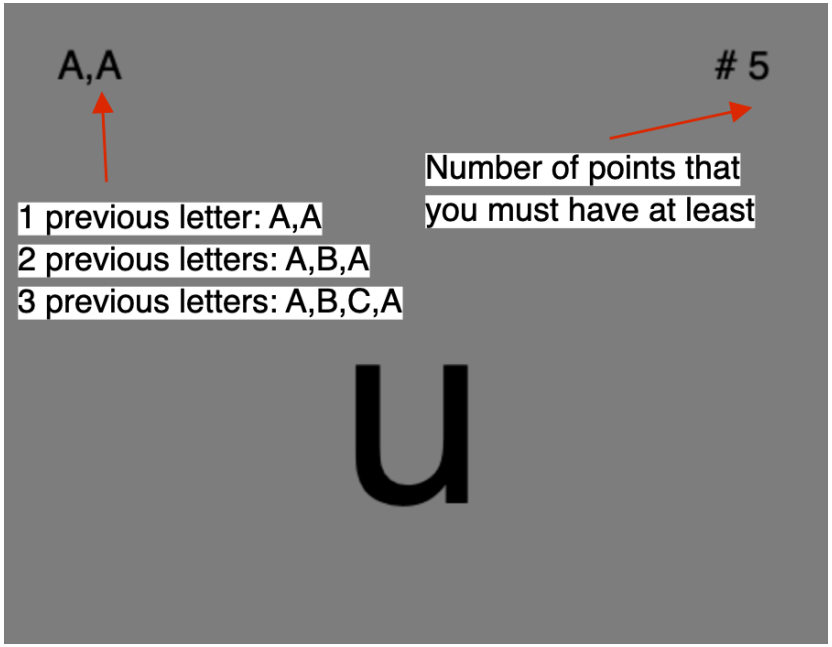
avant) ou A,B,C,A (tâche la plus difficile pour 3 lettres avant).

Dans le coin supérieur droit de l'écran, vous verrez le nombre minimum de points que vous devez avoir pour passer au niveau de difficulté suivant de la tâche.

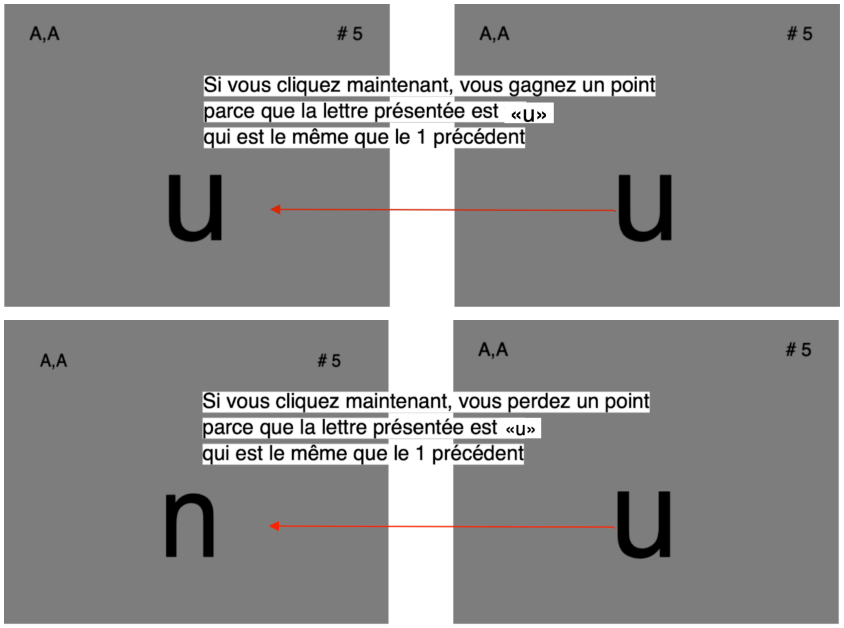


Voici un exemple de tâche simple, c'est-à-dire que vous devez cliquer si vous voyez la même lettre qu'une lettre auparavant. Rappelez-vous que si vous cliquez correctement, vous gagnez un point, si vous cliquez incorrectement, vous perdez un point.

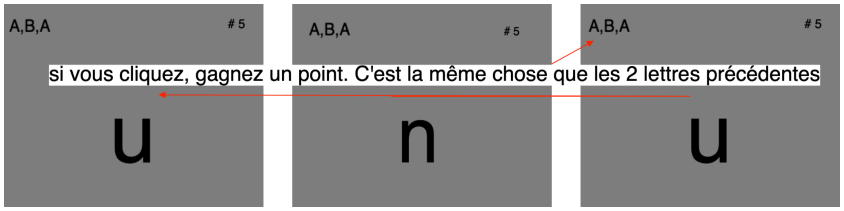
On the right top corner of the screen, you will see the minimum number of points you need to have in order to proceed to the next difficulty level of the task.



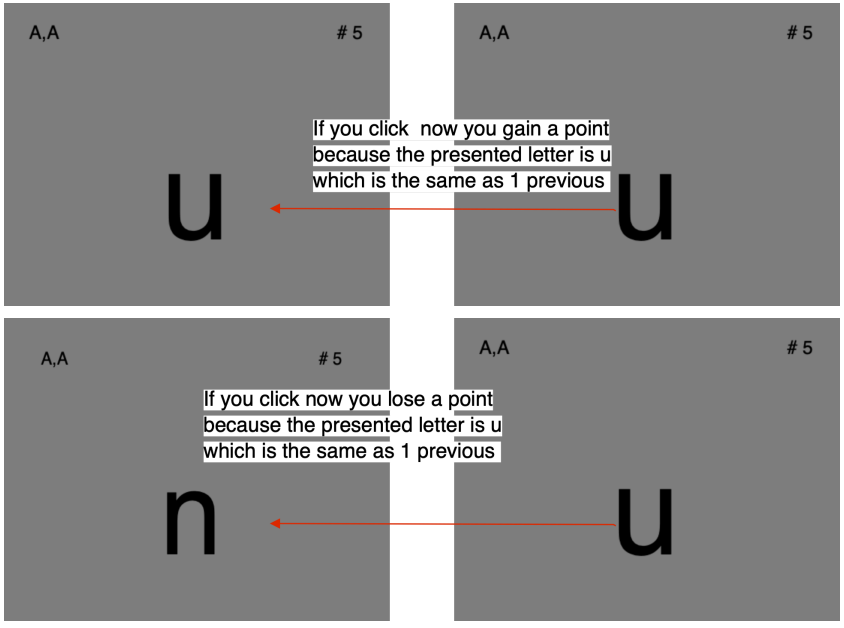
Here is an example of the simple task, that is when you have to click if you see the same letter as just 1 letter before. Remember, if you click correctly, you earn one point, if you click incorrectly, you lose one point.



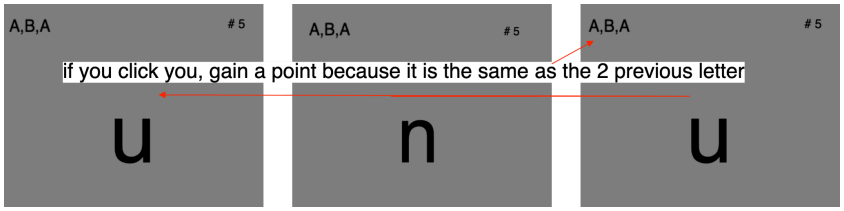
Voici un exemple de tâche de niveau moyen où vous devez cliquer si vous voyez la même lettre que deux lettres précédentes. Si vous cliquez correctement comme dans le cas ci-dessous, vous gagnez un point.



Enfin, voici un exemple de la tâche la plus difficile. Dans l'exemple ci-dessous, vous gagnez un point si vous cliquez

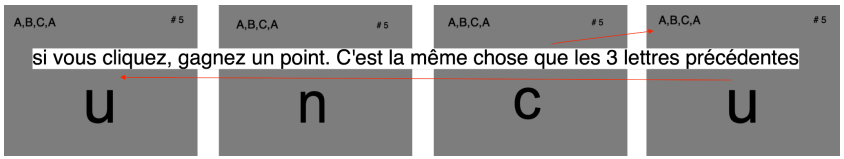


Here is an example of the medium level task when you have to click if you see the same letter as 2 letters before. If you click correctly as in the case below, you earn a point.



Finally, here is an example of the hardest task. In the example below, you earn a point if you click because the letter “u” is the same as three letters before.

parce que la lettre "u" est identique à trois lettres précédentes.



Pour résoudre la tâche, vous devez procéder comme suit :

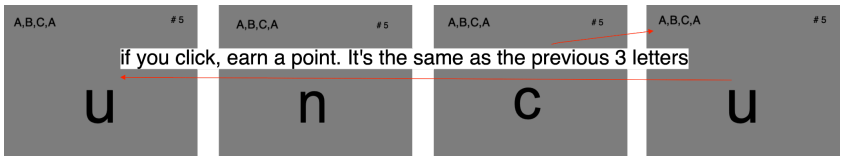
Répétez à voix haute le nombre de lettres que vous voyez dans l'ordre en fonction du niveau de difficulté (par exemple, pour une tâche de niveau moyen, répétez par exemple u-n ; pour une tâche plus difficile, répétez par exemple u-c-n - voir l'exemple ci-dessous).

Vérifiez si la lettre suivante (par exemple m) est la même que la première lettre répétée (dans cet exemple u).

Dans cet exemple, ne cliquez pas car elles ne correspondent pas.

Dans votre esprit, mettez immédiatement à jour votre séquence répétée en supprimant u et en ajoutant m à la fin (ici, u-c-n deviendra c-n-m).

Répétez la même logique pour la lettre montrée suivante (par exemple s) ; vérifiez si le premier élément de la séquence répétée est le même que la lettre montrée tout en mettant à jour votre séquence répétée (par exemple, elle deviendra n-m-s).



To solve the task, you should do the following:

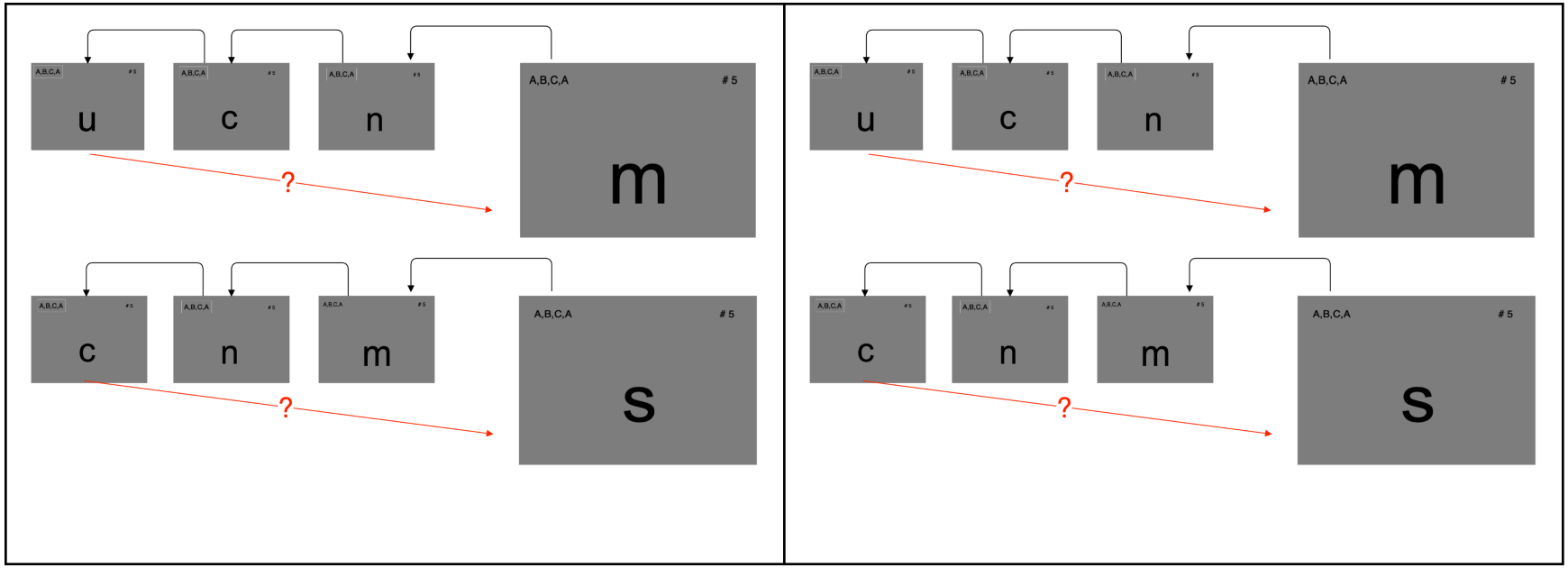
Rehearse by saying out loud the number of letters you see in sequence depending on the difficulty level (e.g. for a medium level task, rehears e.g. u-n; for a hardest task rehears e.g. u-c-n - see the example below).

Check if the following shown letter (e.g. m) is the same as the first rehearsed letter (in this example u).

In this example, don't click as they do not correspond.

In your mind, update immediately your rehearsed sequence by dropping u and adding m and the end (here u-c-n will become c-n-m).

Repeat the same logic for the following shown letter (e.g. s); check if the first item of the rehearsed sequence is the same as the shown letter while updating your rehearsed sequence (e.g. it will become n-m-s).


A,B,C,A
5
u
c
n
m
?
A,B,C,A
5
c
n
m
s
?
A,B,C,A
5
u
c
n
m
?
A,B,C,A
5
c
n
m
s
?

N back (Static)

Dans cette tâche, une série de lettres "u", "c", "n", "m" et "s" est présentée à l'écran.



L'objectif global de la tâche est d'appuyer sur le clic gauche de la souris lorsque vous voyez une lettre que vous avez déjà vue. Si vous cliquez correctement, vous gagnerez un point. Si vous cliquez de manière incorrecte parce que la lettre vue précédemment n'était pas la même que celle qui apparaît actuellement à l'écran, vous perdrez un point. Vous devrez obtenir un nombre minimum de points corrects pour chaque niveau de difficulté de la tâche.

Il existe trois niveaux de difficulté. Dans la tâche la plus simple, vous devez cliquer lorsque vous voyez à l'écran la même lettre que celle que vous avez vue juste une lettre auparavant. Dans la tâche de niveau moyen, vous devez cliquer lorsque vous voyez la même lettre que 2 lettres auparavant. La tâche la plus difficile est celle où vous devez cliquer lorsque vous voyez la même lettre que 3 lettres auparavant (tâche la plus difficile). Nous expliquons

Pour vous rappeler le niveau de difficulté dans lequel vous vous trouvez actuellement, vous verrez dans le coin supérieur gauche de l'écran soit A,A (tâche la plus simple pour 1 lettre avant), A,B,A (tâche moyenne pour 2 lettres

In this task, a series of letters "u", "c", "n", "m", and "s" are presented on the screen.



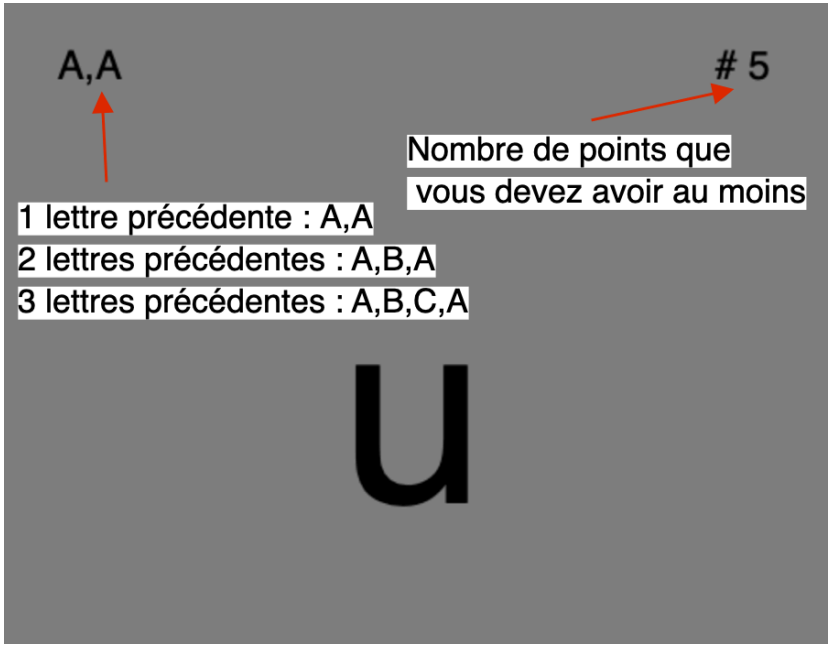
The overall aim of the task is to press the left-hand click of the mouse when you see a letter you have previously seen. If you click correctly, you will earn a point. If you click incorrectly because the previously seen letter was not the same as currently on the screen, you will lose a point. You will have to achieve a minimum number of correct points at each task's difficulty level.

There are three difficulty levels. In the simplest task, you must click when you see the same letter on the screen that you have seen just 1 letter before. In the medium-level task, you must click when you see the same letter as 2 letters before. The hardest task is the one where you have to click when you see the same letter as 3 letters before (hardest task). We will explain

To remind you of the difficulty level that you are currently in, you will see in the left top corner of the screen either A,A (simplest task for 1 letter before), A,B,A (medium task for 2 letters before) or A,B,C,A (hardest task for 3 letters before)

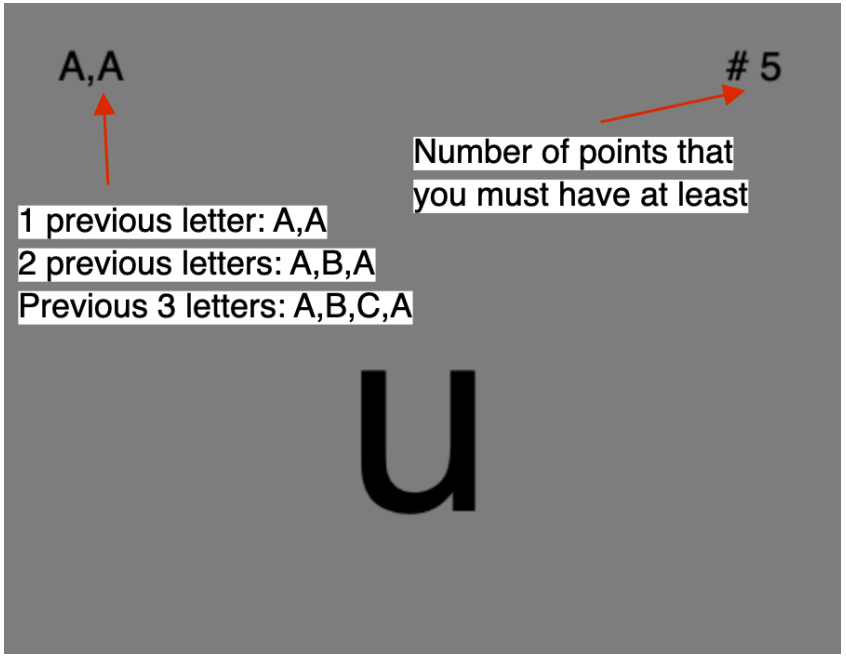
avant) ou A,B,C,A (tâche la plus difficile pour 3 lettres avant).

Dans le coin supérieur droit de l'écran, vous verrez le nombre minimum de points que vous devez avoir pour passer au niveau de difficulté suivant de la tâche.

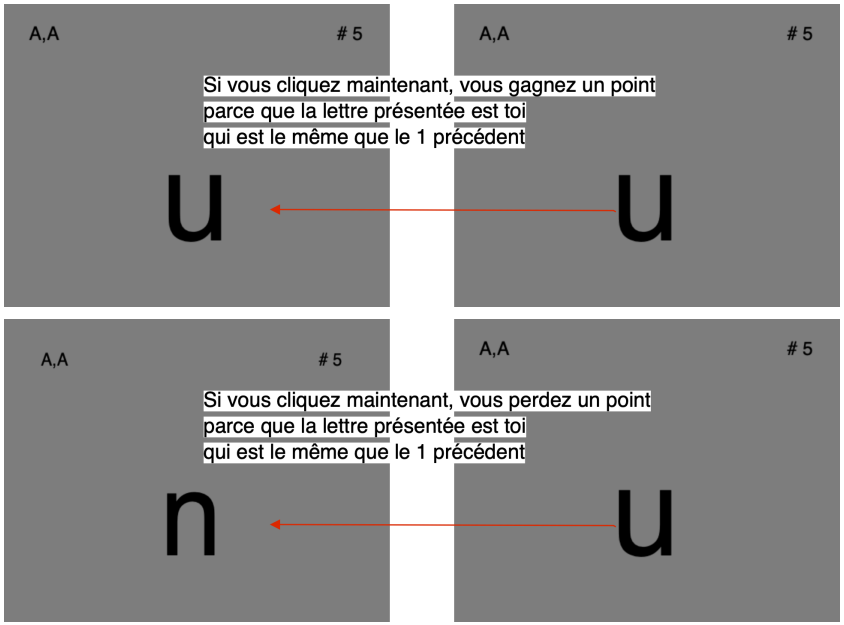


Voici un exemple de tâche simple, c'est-à-dire que vous devez cliquer si vous voyez la même lettre qu'une lettre auparavant. Rappelez-vous que si vous cliquez correctement, vous gagnez un point, si vous cliquez incorrectement, vous perdez un point.

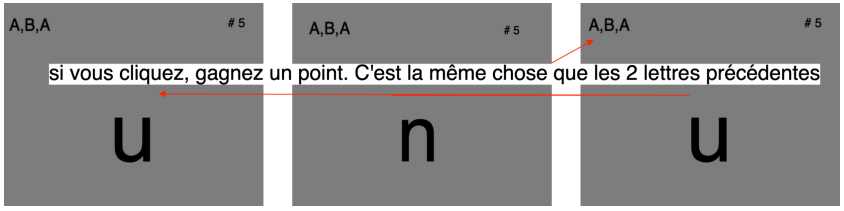
On the right top corner of the screen, you will see the minimum number of points you need to have in order to proceed to the next difficulty level of the task.



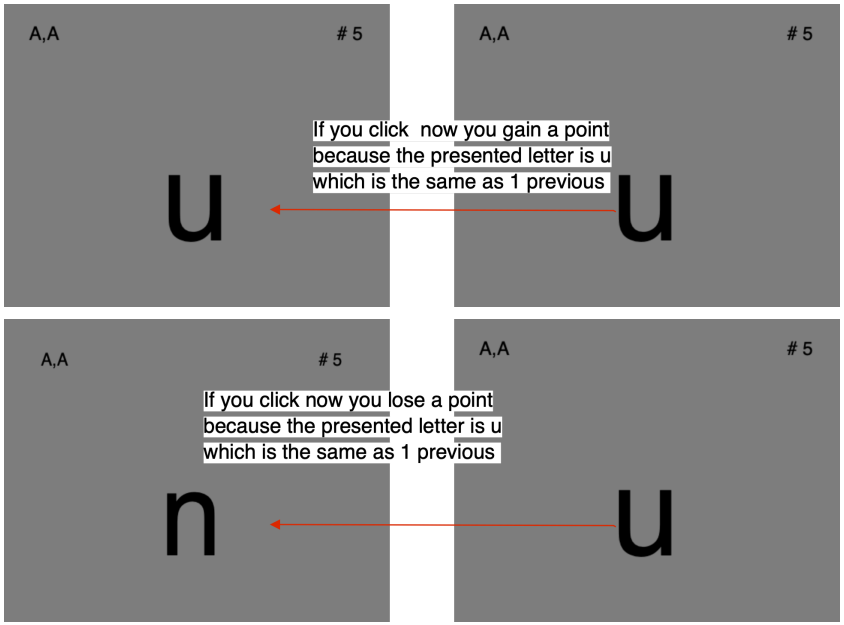
Here is an example of the simple task, that is when you have to click if you see the same letter as just 1 letter before. Remember, if you click correctly, you earn one point, if you click incorrectly, you lose one point.



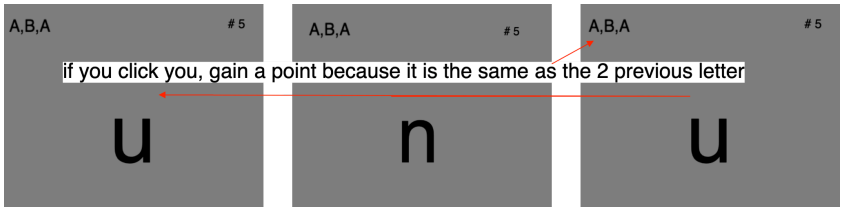
Voici un exemple de tâche de niveau moyen où vous devez cliquer si vous voyez la même lettre que deux lettres précédentes. Si vous cliquez correctement comme dans le cas ci-dessous, vous gagnez un point.



Enfin, voici un exemple de la tâche la plus difficile. Dans l'exemple ci-dessous, vous gagnez un point si vous cliquez

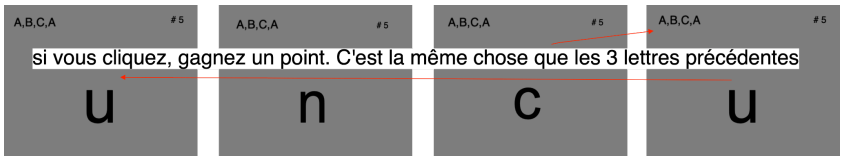


Here is an example of the medium level task when you have to click if you see the same letter as 2 letters before. If you click correctly as in the case below, you earn a point.



Finally, here is an example of the hardest task. In the example below, you earn a point if you click because the letter “u” is the same as three letters before.

parce que la lettre "u" est identique à trois lettres précédentes.



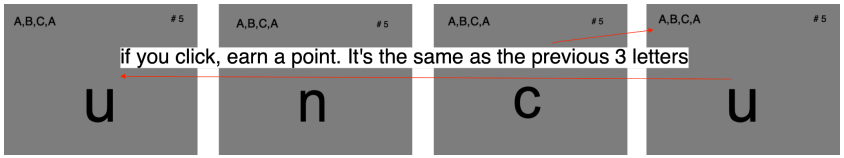
Pour résoudre la tâche, vous devez procéder comme suit : Répétez en disant à haute voix le nombre de lettres que vous voyez dans l'ordre en fonction du niveau de difficulté (par exemple, pour une tâche de niveau moyen, répétez par exemple u-n ; pour une tâche plus difficile, répétez par exemple u-c-n comme dans l'exemple ci-dessous).

Vérifiez si la lettre suivante (par exemple m) est la même que la première lettre répétée (dans cet exemple u).

Dans cet exemple, ne cliquez pas car elles ne correspondent pas.

Dans votre esprit, mettez immédiatement à jour votre séquence répétée en remplaçant u par m (ici u-c-n deviendra m-c-n).

Répétez la même logique pour la lettre montrée suivante (par exemple s) ; vérifiez si le deuxième élément de la séquence répétée est identique à la lettre montrée tout en mettant à jour votre séquence répétée (par exemple, elle deviendra m-s-n).



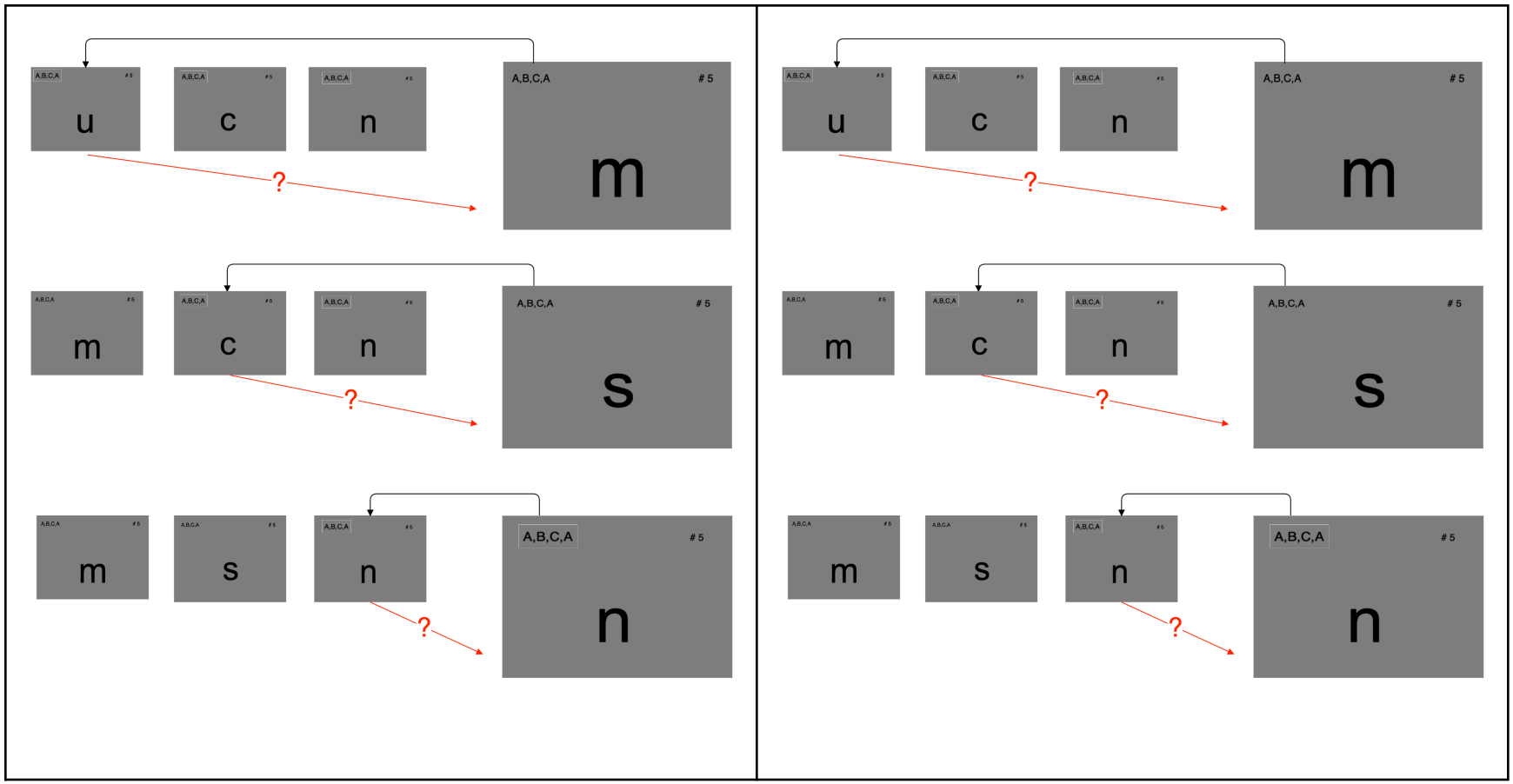
To solve the task, you should do the following:
Rehearse by saying out loud the number of letters you see in sequence depending on the difficulty level (e.g. for a medium level task, rehears e.g. u-n; for a hardest task rehears e.g. u-c-n as in the example below).

Check if the following shown letter (e.g. m) is the same as the first rehearsed letter (in this example u).

In this example, don't click as they do not correspond.

In your mind, update immediately your rehearsed sequence by replacing u with m (here u-c-n will become m-c-n).

Repeat the same logic for the following shown letter (e.g. s); check if the second item of the rehearsed sequence is the same as the shown letter while updating your rehearsed sequence (e.g. it will become m-s-n).



A,B,C,A
5
u
c
n
m
?
m
c
n
s
?
m
s
n
n
?
u
c
n
m
?
m
c
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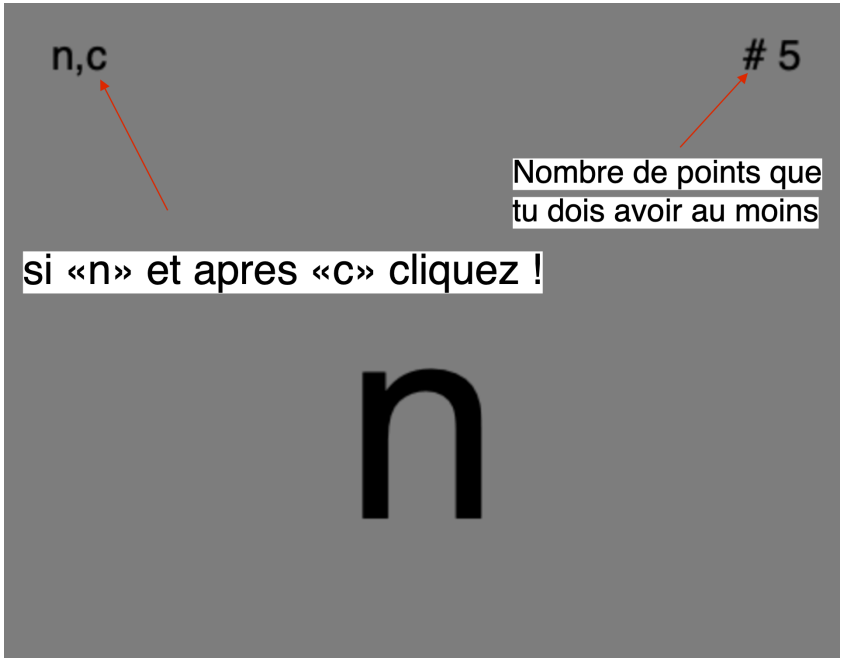
?
m
s
n
n
?

AX-CPT (Proactive)

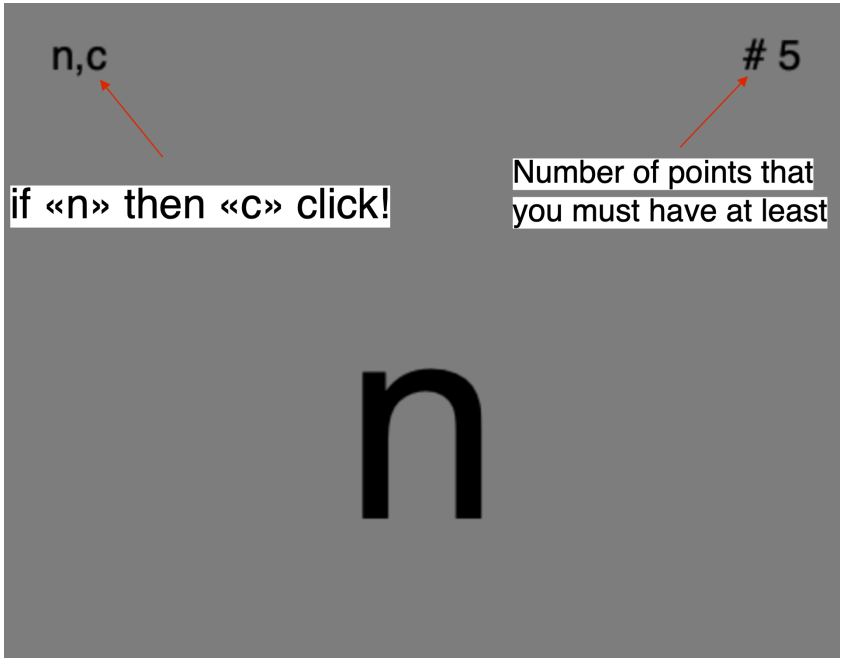
Dans cette tâche, une série de lettres "u", "c", "n", "m" et "s" sont présentées à l'écran.

Chaque fois que vous voyez la lettre "c" après la lettre "n", vous devez appuyer sur le clic gauche de la souris pour gagner un point. Si vous vous trompez en cliquant sur la souris, vous perdez un point. Dans le coin supérieur droit de l'écran, vous verrez le nombre minimum de points que vous devez avoir pour passer au tour suivant de la tâche.

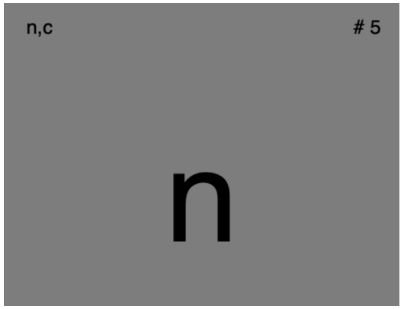


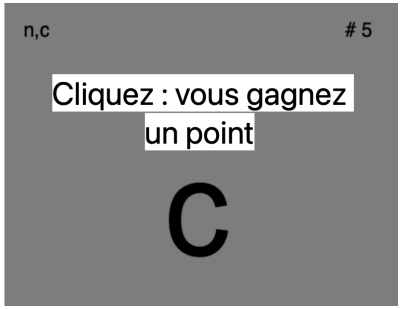
In this task, a series of letters "u", "c", "n", "m", and "s" are presented on the screen.

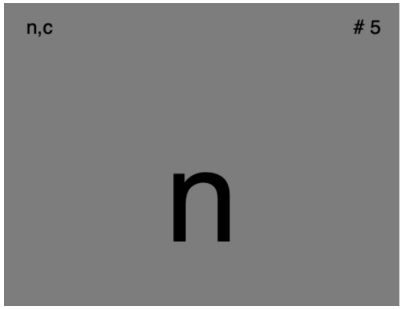
Each time when you see the letter "c" after the letter "n", you should press the left click of the mouse to gain one point. If you incorrectly click on the mouse, you lose a point. On the right top corner of the screen, you will see the minimum number of points you need to have to proceed to the next round of the task.

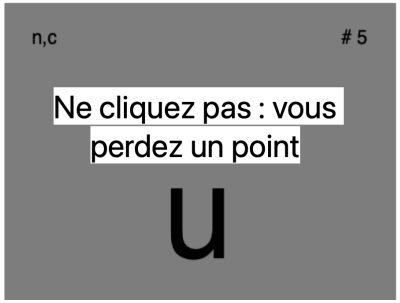


Pour résoudre la tâche, vous devez faire ce qui suit :
Lorsque vous voyez la lettre "n", préparez-vous à cliquer si vous voyez la lettre "c" !

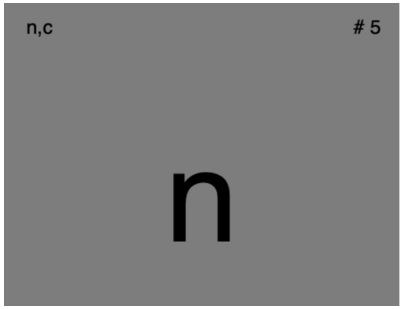


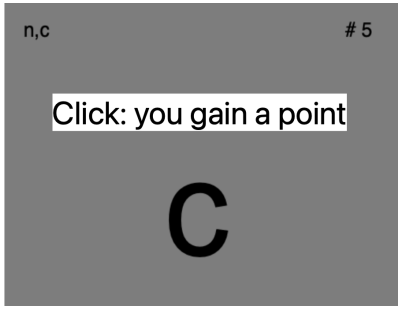


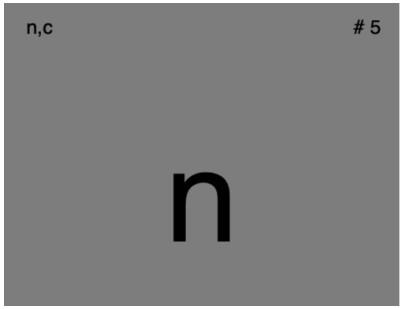


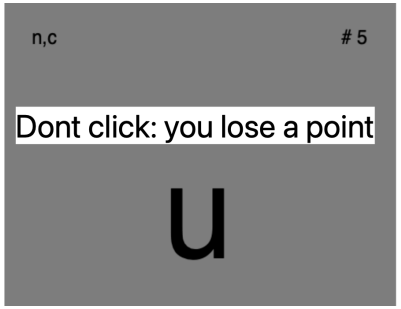


To solve the task, you should do the following:
When you see the letter “n”, be prepared to click if you see the letter “c”!





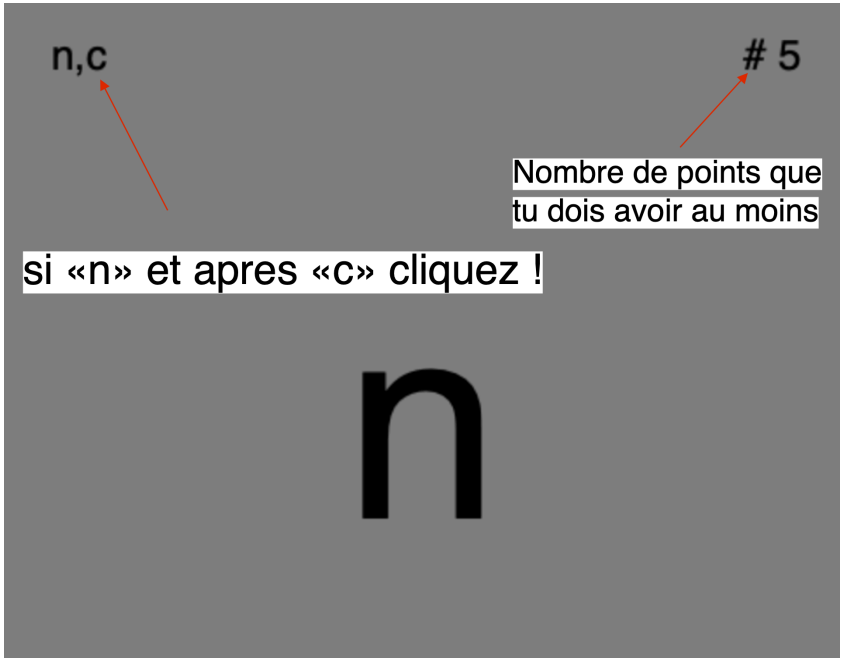




AX-CPT (Reactive)

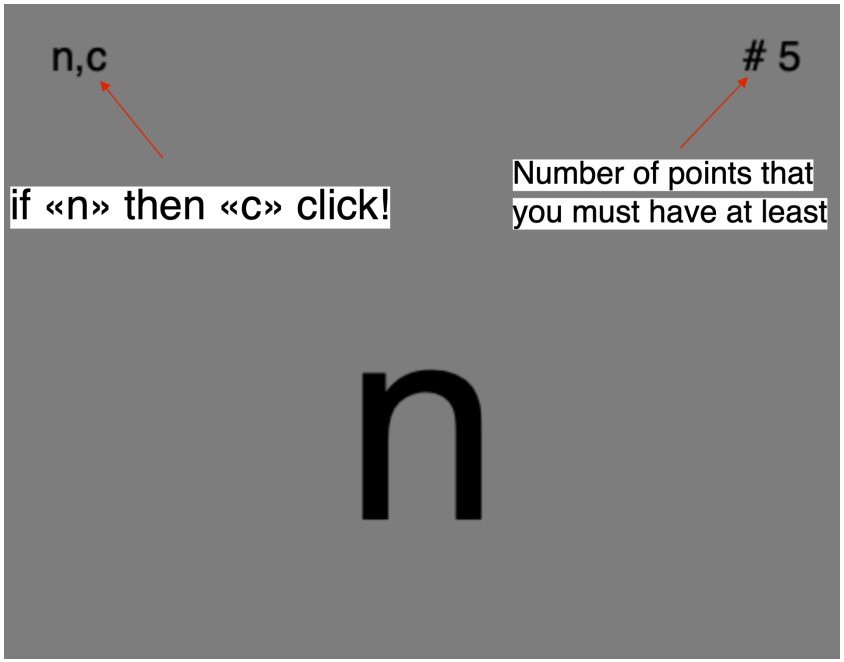
Dans cette tâche, une série de lettres "u", "c", "n", "m" et "s" sont présentées à l'écran.

Chaque fois que vous voyez la lettre "c" après la lettre "n", vous devez appuyer sur le clic gauche de la souris pour gagner un point. Si vous vous trompez en cliquant sur la souris, vous perdez un point. Dans le coin supérieur droit de l'écran, vous voyez le nombre minimum de points que vous devez avoir pour passer au tour suivant.



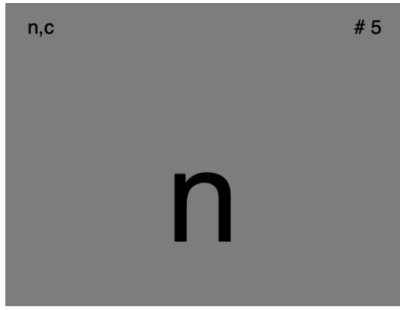
In this task, a series of letters "u", "c", "n", "m", and "s" are presented on the screen.

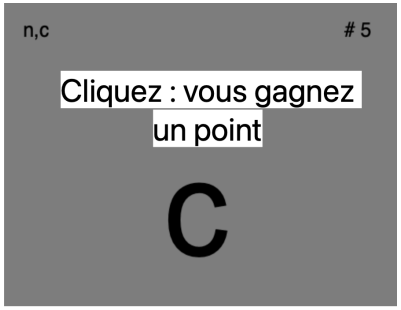
Each time when you see the letter "c" after the letter "n", you should press the left click of the mouse to gain one point. If you incorrectly click on the mouse, you lose a point. On the right top corner of the screen, you see the minimum number of points you need to have to proceed to the next round.

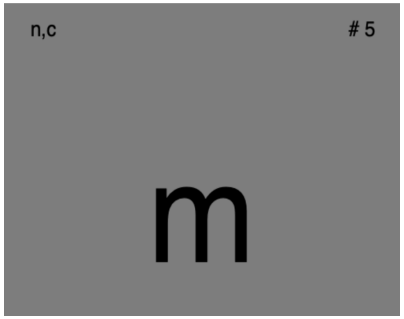


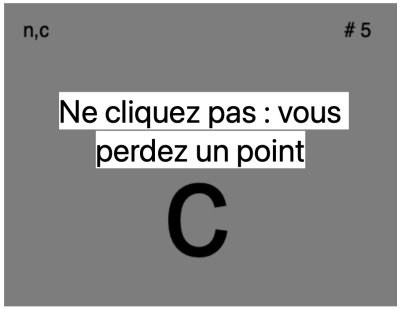
To solve the task, you should do the following:

Pour résoudre cette tâche, vous devez procéder comme suit : Lorsque vous voyez la lettre "c", rappelez-vous si la lettre précédente était "n", puis décidez de cliquer ou non !

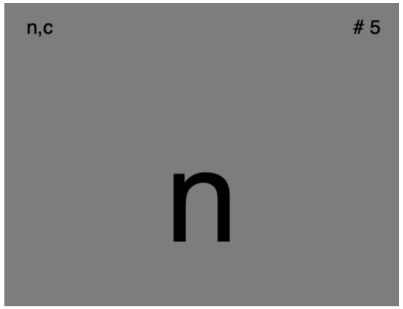


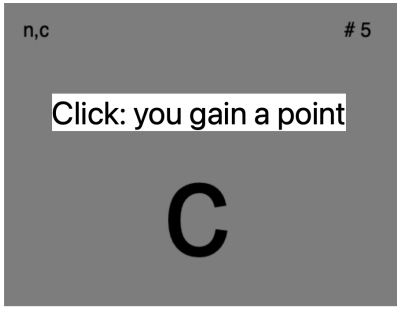


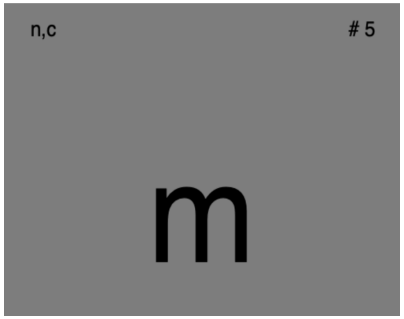


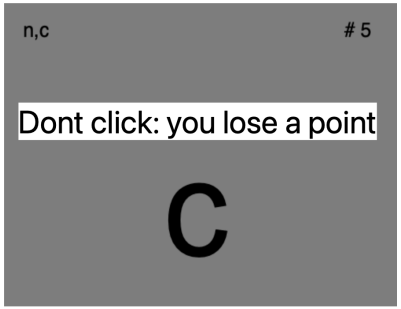


When you see the letter “c”, remember if the previous letter was “n”, then decide to click or not!









Que devriez-vous dire ?

1-back

u	n	u	m	u	u	m	c	c	u	n	m

2-back

u	c	m	n	u	c	m	c	c	u	n	m

3-back

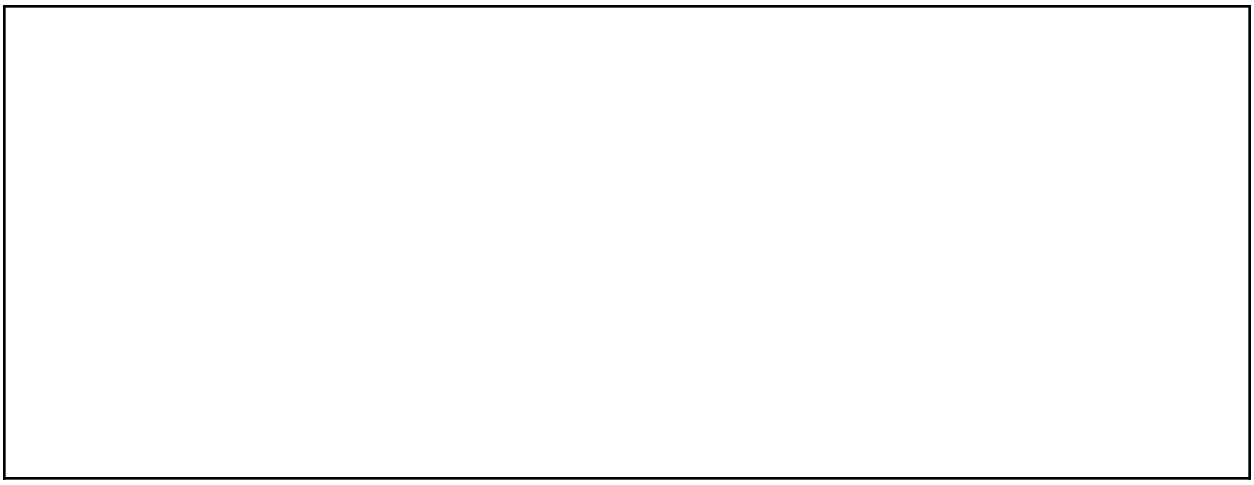
u	c	m	n	u	c	m	c	c	u	n	m
u	n	u	m	u	u	m	c	c	u	n	m

Debriefing (Protocol.....Sujet.....)

From 1 to 10 how much did you like the task? Sur une échelle de 1 à 10, dans quelle mesure avez-vous apprécié la tâche?
Would you say that your thoughts were focused or diffuse? Diriez-vous que vos pensées étaient concentrées ou diffuses ?
Were you doing other mental activities than the task during the experiment? (if so , what and when?) Faisiez-vous d'autres activités mentales que la tâche pendant l'expérience ? (si oui, lesquelles et quand ?)
If applicable, did you rate the effort of only the task or also your other mental activities? Le cas échéant, avez-vous évalué l'effort fourni uniquement pour la tâche ou également pour vos autres activités mentales ?
Did you apply the strategy all along, or did you do otherwise at time? Would you say the strategy changed the effort you needed to accomplish the task? Avez-vous appliqué la stratégie depuis le début ou avez-vous agi différemment à un moment donné ? Diriez-vous que la stratégie a modifié l'effort que vous avez dû fournir pour accomplir la tâche ?

Were you able to predict your score? Did the score affect your performance and judgements? Did the criteria of minimal score affect how you performed the task? Avez-vous été en mesure de prévoir votre score ? Le score a-t-il influencé votre performance et vos jugements ? Les critères d'un score minimal ont-ils influencé la manière dont vous avez exécuté la tâche ?
Did you feel that your perception of effort and your perception of valence and arousal were related? In what way? Avez-vous eu l'impression que votre perception de l'effort et votre perception de la valence et de l'excitation étaient liées ? De quelle manière ?
Did your perception of effort , valence or arousal change over the course of the experiment? How? Votre perception de l'effort, de la valence ou de l'excitation a-t-elle changé au cours de l'expérience ? De quelle manière ?
What are the difficulties that you met when applying the strategy? Quelles sont les difficultés que vous avez rencontrées lors de l'application de la stratégie ?

Did you have a clear notion of what you were rating in your judgments of effort? In general, what words come to your mind when you hear “mental effort”? Aviez-vous une idée claire de ce que vous évaluiez dans vos jugements sur l'effort ? En général, quels mots vous viennent à l'esprit lorsque vous entendez "effort mental" ?
How did you find out about the experiment and the study and what was your reason for volunteering? Comment avez-vous eu connaissance de l'expérience et de l'étude et quelle est la raison pour laquelle vous vous êtes porté volontaire ?
Could you list an activity that would require very high mental effort for you? And very little? Pourriez-vous citer une activité qui vous demanderait un effort mental très important ? Et très peu ?
would you say effort is costly? (if applicable, why didn’t you reflect it as negative valence) Fin de la deuxième session : diriez-vous que l'effort est coûteux (le cas échéant, pourquoi ne l'avez-vous pas considéré comme une valence négative) ?



Training Comments

“Try to click less! Not to lose points”
“Refresh more and start over more”
“You can rehearse however you want with a lower tone and simpler or shortened sound. The only important things are to update your rehearsal by the instruction of strategy and check with the trial to click at the right time”
“It is okay, everyone has trouble solving this task. It is designed deliberately to be so challenging and hard”
“You are doing a great job!”

"Essayez de cliquer moins ! Ne pas perdre de points"
"Rafraîchissez plus et recommencez plus"
"Vous pouvez répéter comme vous le souhaitez avec un ton plus bas et un son plus simple ou plus court. La seule chose importante est de mettre à jour votre répétition en suivant les instructions de la stratégie et de vérifier avec l'essai que vous cliquez au bon moment.
"Ce n'est pas grave, tout le monde a du mal à résoudre cette tâche. Elle est délibérément conçue pour être aussi difficile et stimulante.
"Vous faites du bon travail !"