Understanding Effort-Based Decisions: The Role of Domain, Competence, and Enjoyment

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Abstract

Leading motivation theories stipulate that decision-making involves a cost-benefit analysis of potential behaviours. Effort plays an important role in this process by mediating the expected value of candidate tasks. The first two chapters of this thesis concern what effort is, and how it can be measured. I propose effort to reflect a willingness to endure cost, and that measures deriving from behavioural economics are the most intuitive way to quantify this cost function. In the following two chapters I present empirical data. Firstly, I investigate whether physical effort is controlled by different mechanisms to cognitive effort (N = 93). Findings reveal that effort willingness, as measured with an effort discounting task, did not differ between cognitive and physical tasks but instead varies in a dual-task scenario, suggesting that effort relies on a common system. In follow-up factor analyses based on self-reported effort exertion for daily activities (N = 381, 348, 48), we again found weak support for a domain-specific effort. I then investigate the roles of competence and enjoyment for effort willingness, by comparing effort willingness for two versions of the same auditory discrimination task, where sound stimuli were either music or language-related sounds (N = 106). The music-related version was perceived as more enjoyable and engaging, while there was no difference in competence nor subjective value. Notably, perceived, and actual competence predicted effort, unlike enjoyment and engagement. An exploratory factor analysis again on self-reported effort, supported these findings by showing that effort was best classified in terms of perceived competence and task frequency. Finally, I reflect upon and critically review the five studies. I conclude that focus should be placed on competence and experience, rather than whether the task is cognitive, physical, or enjoyable. Future studies should investigate not only effort level, but the plasticity of effort over time.

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Contents

Abbreviations

Attention-Deficit Hyperactivity Disorder (ADHD)

Cognitive Effort Discounting Task (COG-ED)

Cognitive Effort Expenditure for Rewards Task (C-EEfRT)

Cognitive Effort Motivation Task (CEMT)

Confirmatory Factor Analysis (CFA)

Demand Selection Task (DST)

Ecological Momentary Assessment (EMA)

Effort Discounting Task (EDT)

Effort Expenditure for Rewards Task (EEfRT)

Expected Value of Control (EVC)

Exploratory Factor Analysis (EFA)

Motivation Intensity Theory (MIT)

Need For Cognition (NFC)

Positron Emission Tomography (PET)

Reaction Time (RT)

Subjective Value (SV)

University of East Anglia (UEA)

Authors Declaration

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas, and contributions from the work of others. Necessary permission has been gained for use of all Figures used in the current thesis. For Figure 1, both the Journal and lead author have given express written permission. Figure 2 is covered under the original Nature Communications articles Creative Commons license, and so is credited where necessary. Permission for Figures 3 and 5 were gained through RightsLink, a service used by Brain and Cognitive, Affective, & Behavioral Neuroscience respectively. All are given attributed to their respective articles where used. No other figures herein require external permission for use.

The research presented in Chapter Three has been presented as a poster presentation, at the University of East Anglia PGR Conference, and has been prepared for Journal submission. The research presented in Chapter Four has been presented as a poster presentation and prepared for Journal submission. As well as the research in this thesis, I have also prepared my master's thesis relating to the impact of ownership and self-relevance on working memory for Journal submission.

During my studies, I undertook a three-month internship as a Cognitive Scientist at Cambridge Cognition, where I rapidly developed and deployed a novel executive function task for mobile using PsychoPy. A poster presentation of my work was later presented by the company at the International Society for CNS Clinical Trials and Methodology (ISCTM) 2023 in Spain. Now, as part of my full-time position as a cyber behaviour analyst for a private cyber security company in London, I conduct research and produce industry reports centred around understanding, measuring, and changing cyber behaviours.

Publications

Casey, L. J., Dewsnip, S., & Pavitt, S. (2024). National Cyber Risk Relates to Human Development: Could Cyber Behaviours be the Key to Unlocking Human Development? [Industry report]. Retrieved from https://recyber.com/national-cyber-risk-relates-to-human-development/

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Statement on the Impact of the Covid-19 Pandemic

Part of my original doctoral programme was impacted by the restrictions resulting from the COVID-19 pandemic. The pandemic resulted in national lockdowns and laboratory closures between March 2020 and May 2021. I received a 3-month extension in my funding and submission date as a result. As my doctoral studies began October 2019, the lockdowns severely impacted my research plans and considerably pushed back my data collection. Additionally, I had originally planned to collect data from Norwich City Football club, as it is a world level football club in our city with ties to UEA. I had agreements in place with the liase between the university and the club. The research was going to assess the domain specificity of effort for experts, for tasks related to their domain of expertise and otherwise. The plan was to then compare this to a control group from a non-athlete population. However, as a direct consequence of the pandemic, the club were understandably unwilling to go ahead, and so we proceeded with more general tasks in a predominantly student population with a socially distanced procedure that now makes up Study 1.

CHAPTER ONE: WHAT IS EFFORT?

Introduction

As effort is ubiquitous in daily life, researchers in many disciplines, namely behavioural economics, marketing, and psychology, have taken an interest in its study. For example, in behavioural economics, the concept of bounded rationality is thought to influence decisions to exert effort, whereby rational decision-making is conceptualised as not merely a person's ability to make good choices with the most favourable outcomes, but rather also to account for thinking capacity and the cost of deciding (Simon, 1990). In marketing and psychology, dual process theories have also been pervasive. Such theories distinguish between two types of thinking, one that is primarily characterised as being effortful, and one that is effortless (Kahnemann & Frederick, 2002). By understanding cognitive processes in this way, researchers have been able to more clearly understand and influence consumer behaviour, boost brand recognition, and optimise advertising and product design. It has also allowed psychologists to explore how automatic and controlled processes influence outcomes across a range of fields such as memory, perception, and decision-making. In addition, the idea that people avoid effort when making inferences about others and social situations, is pervasive in social psychology (Fiske & Taylor, 1991).

In this opening chapter, I begin by highlighting the importance of effort for various outcomes. I then draw out three key questions in the field and dedicate the remainder of the chapter to addressing them. The primary goal of this thesis is to understand how cognitive and physical efforts relate, as well as what aspects besides from domain influence effort-based decisions. This opening chapter supports this central goal by providing a theoretical understanding of what effort is and therefore how effort willingness may vary between and within tasks.

The Relevance of Effort

Broadly, effort is typically thought to play a role in mediating the degree of purposeful engagement with an action or demanding task (Westbrook & Braver, 2015). Engaging in effortful tasks, or the propensity to do so, has been related to several desirable outcomes, such as the attainment of long-term goals (Duckworth et al., 2007), increased career progression (Nabi, 1999), more positive attitudes towards tasks requiring reasoning or problem solving (Cacioppo, et al., 1996), and higher quality financial decisions (Smith & Walker, 1993). Additionally, conscientiousness and engagement have been shown to largely determine educational performance (Cacioppo et al., 1996; von Stumm, et al., 2011), which both heavily rely on the exertion of effort. Relatedly, exerting high physical effort can result in feelings of control over personal actions and consequences (Demanet, et al., 2013), act as a bodily trigger to put more effort into cognitive tasks (Jostmann et al., 2009), result in better cardiovascular health (Beckner & Winsor, 1954; Shiroma & Lee, 2010), and improve overall quality of life (Conn, et al., 2009). For example, in the study by Jostmann and colleagues, it was found that holding a heavy clipboard, compared to a light one, led to increased perceived importance of instructions as well as greater elaboration of thought. Given the relationship between weight and importance, they proposed there to be a direct mental association between sensory experiences of weight and investments of mental effort. Such a study demonstrates the relevance of considering both cognitive and physical efforts.

Effort may also play a key role in many neuropsychiatric disorders, namely Attention-Deficit Hyperactivity Disorder (ADHD; Volkow et al., 2011), schizophrenia (Strauss et al., 2016), and depression (Cohen et al., 2001). For example, willingness to engage in more highly rewarding effortful tasks compared to lesser rewarding easier tasks has been shown to be lower in those with major depressive disorder compared to healthy controls (Treadway et al., 2012a), in those with greater depression severity and anhedonic symptomology (Barch et al., 2014), in patients with schizophrenia compared to demographically matched controls (Gold et al., 2015), and be greater in patients with autism spectrum disorder (Damiano et al., 2012). It is widely believed that an improved conceptual understanding of what is meant by effort will assist in the detection and diagnosis of such disorders, and perhaps inform new strategies for treatment (Chong et al., 2016). For instance, as mentioned previously, one primary symptom of major depressive disorder is an unwillingness to expend effort to gain rewards (Hartlage et al., 1993; Treadway et al., 2012). Therefore, effort is likely relevant to study in understanding why individuals with depression often underperform on high cognitively demanding tasks compared to control groups but perform equally well during lower demand conditions (Hammar & Årdal, 2009).

However, despite the relevance of effort, no unified and widely accepted definition exists in the literature (Thomson & Oppenheimer, 2022; Westbrook & Braver, 2015). For example, effort has been referred to in many ways, such as cognitive efficiency, cognitive capacity, processing capacity, cognitive resources, physical fatigue, energetic costs, and workload. Such terms are often used interchangeably (e.g., Tyler et al., 1979), or are used for different purposes (Kahneman, 1973; Simon, 1990). Thomson and Oppenheimer (2022) argue that due to the numerous definitions and intuitive interpretations of effort on offer, an illusion of understanding with regards to effort has emerged. They argue that this prevents researchers from asking fundamental questions about effort, and from being critical of the underlying differences in their perspectives. I agree with this assessment and propose that a chapter devoted to what we mean by effort is justified and needed given the current state of the literature.

The Three Questions

For many years, researchers interested in decision-making relied on the assumption that the mental strategies people use, and the biases that result, stem from a desire to minimise effort expenditure (Ferrero, 1984; Kurzban et al. 2013). This assumption was based on the Law of Less work (Hull, 1943), whereby individuals are described as possessing an innate desire to minimise effort expenditure unless incentivised otherwise by biological or physiological needs. Subsequently, many approaches, such as the information-processing approach (Payne & Bettman, 2004) and the fast-and-frugal approach (Gigerenzer, et al., 1999), assume that the mental processes that people use represent the downstream effects of effort conservation. Despite many theories of effort relying on this assumption, studies fail to directly show that the strategies in question conserve effort at all (Shah & Oppenheimer, 2008). Furthermore, this basic notion fails to account for individuals who repeatedly seek out effortful situations (Cacioppo & Petty, 1982).

To define effort more precisely, it has recently been proposed that researchers should consider their response to at least the following three key questions relating to effort (Shepard, 2021). Firstly, to what extent is effort independent from other related constructs? For example, how does effort relate to motivation and cognitive control? Secondly, to what extent is effort aversive and why? What is it about effort that makes it costly? Are there instances where effort is not costly? Finally, what is the function of effort? What functional role does effort play, and why do individuals not always engage maximal effort? The goal of this chapter is to consider and discuss evidence related to these three questions relating to effort, with the overarching goal being to present a workable definition of effort.

In the aim to find a common definition of effort, what do we need to consider? We firstly need to consider that the answers to the above three questions are not mutually exclusive. For example, while the function of effort could be hypothesised to be to preserve a precious resource, and thus align with the view that the aversiveness of effort relates to the depletion of such a resource, this does not have to be the case. For example, it could equally be that the function of effort is to preserve a precious resource, but that the aversiveness of effort is instead related to rising opportunity costs. Due to this, there are many possible combinations for which these questions can be addressed.

We also need to consider that while most definitions of effort define it for cognitive tasks (Kool et al., 2010; Westbrook & Braver, 2015), the use of the term effort is also often associated with physical exertion (Massin, 2017), where physical effort emerges from the performance of motor actions (Morel et al., 2017). As highlighted by Andre et al. (2019), there is a growing interest in the literature regarding whether effort should be considered a single construct applied to tasks across domains, or whether cognitive and physical should be considered separately. Most researchers have considered effort to be the former. This is because physical exercise has been shown to deplete executive control, especially among those with low physical fitness (Labelle, et el., 2014). Additionally, different types of effort share similar phenomenology (Székely & Michael, 2021). For example, individuals engaging in both cognitive and physical tasks often describe the 'feeling' of effort. Additionally, both can be influenced by motivational factors (e.g., reward), can result in feelings of reward, and tend to result in fatigue. As a result, Andre et al (2019) consider physical effort to just be mental effort applied to physical exertion for the duration of the task.

However, in a review of cognitive versus physical fatigue, Barnes and Van dyne (2009) point to differences in how physical and cognitive effort over time leads to differing impacts on self-efficacy. They highlight that in contrast to a weak relationship found between physical fatigue and self-efficacy beliefs (Baranski et al., 1998), cognitive fatigue has a strong effect on self-efficacy beliefs, with fatigued individuals typically estimating themselves to have lower competence (Maslach et al., 2000). The topic of domain specificity (e.g., how effort relates for cognitive versus physical tasks) is a key topic that is further explored in Chapter Three of this thesis, though for now both 'types' of effort will be referred to interchangeably. The primary focus of this opening Chapter is instead to explicitly define effort, by critically considering it in terms of its independence, aversiveness, and function.

To What Extent is Effort Independent from Other Related Constructs?

When defining effort, it is important to firstly consider how it relates to other constructs. Analogously to how researchers advocating for the importance of grit, the sustainment of effort over long periods of time, defined grit in relation to motivation and talent (Duckworth et al., 2007), I will unpack, based on the existing literature, how effort relates to attention, fatigue, task difficulty, risk, grit, need for cognition (NFC), cognitive control, motivation, pain intelligence, and anxiety. Chapters Three and Four will provide empirical data on how effort relates to this network of related constructs, from studies conducted within this thesis.

Attention

Attention is typically defined as the process of selecting the information that gains access to working memory, and is thought to be made up of four processes; working memory, top-down sensitivity control, competitive selection, and bottom-up filtering of salient stimuli (Knudsen, 2007). It is possible that effort refers to the competitive selection aspect of attention, as this process determines which information gains access to working memory (Desimone & Duncan, 1995). In such a view, effort is the result of load on the attentional system, meaning that high effort engaged in a task may aid performance via increased attention.

In Chapter Two of his seminal work on effort and attention, Kahneman (1973) argues that pupil responses reflect both attention and effort. For pupil responses to reflect a measure of effort, Kahneman argued that they must be sensitive to task demands, as well as variations in participant's effort during task performance. In support of this argument, he points to the wealth of pupillometry studies showing a close correlation between participant attention and effort. Specifically, such studies show both the amount of dilation to increase with task demand or difficulty, as well as to reflect the participants momentary involvement in the task during performance (see Goldwater, 1972 for a review). Therefore, he identified them both to be an investment of resources in an occurrent cognitive activity. Due to the sheer volume of studies showing a tight coupling between effort and attention, the notion of effort and attention being closely related remains, and has led some researchers to consider them to be one and the same (Sarter et al., 2006).

While it is true that many tasks requiring effort also require attention, Kahneman's work on the relationship between effort and attention is now broadly considered to lack operationalised terms and ecological validity (Bruya & Tang, 2018). For example, 'effort' is not clearly defined and so it is not clear how it is measured or manipulated. Additionally, much of Kahneman's work was conducted in specific laboratory settings, meaning that the set ups were artificial and that the findings may not generalise to everyday situations. As well as being conducted in a lab, many of the tasks used by Kahneman such as arithmetic, short-term memory and pitch discrimination tasks are simplified versions of real-life scenarios, and so again may lack ecological validity. Additionally, many studies have since shown that effort and attention can be both positively and negatively correlated. For example, Bruya (2010) highlight in their book that under certain conditions, such as when individuals are experts in a certain domain or when in a meditative state, that attention can be subjectively experienced as effortless.

Consequently, rather than being one and the same as hypothesised by Kahneman (1973), effort and attention are typically no longer viewed synonymously in the effort literature, but rather as two closely related but fundamentally separate constructs. The dominant viewpoint in the literature today is that there are two distinct modes of attention, the first of which is subjectively effortful top-down voluntary attention that is directed based on prior knowledge or current goals to handle task demands. The second mode is bottom-up involuntary attention that is primarily driven by external factors such as stimuli, that may be experienced as effortless (Kaplan & Berman, 2010; Katsuki & Constantinidis, 2014). Therefore, while the two may be comorbid, particularly in the first mode of attention described, they do not necessarily have to be, and represent distinct constructs. Dissociating between effort and attention helps to understand activities that people choose to do in their downtime such as playing video games, that are often not experienced as effortful, but require high attention, and can often be experienced as a break from other activities requiring high attention that are subjectively more effortful (Bruya & Tang 2018). A distinction between effort and attention is also foundational to concepts such as flow, which is classically considered to be a subjectively effortless state of high attention (Csikszentmihalyi, 1975).

Fatigue

Another construct often shown to correlate with effort is fatigue (Hockey & Hockey, 2013). This is because highly effortful tasks, particularly physical tasks, tend to also be fatiguing. However, many researchers conceptualise them as separate, due to observations of effort increasing, decreasing, and remaining unaffected by fatigue (Brehm & Self, 1989). For example, effort can increase despite fatigue such as when a task still seems possible. Alternatively, effort can reduce in response to fatigue when it is apparent that success is excessively difficult. In further contrast, fatigue may have no effect on effort when the task is viewed as impossible regardless of fatigue. For example, consider an individual's completion of a marathon. It is equally possible that they continue to exert effort throughout, believing that they can complete the distance, stop running along the way if they feel incapable of finishing, or not even begin the distance regardless of fatigue as they estimate the task to be impossible. In line with the idea that effort and fatigue are separate, in a study assessing the effect of interest on effort and fatigue, Milyavskaya et al. (2018) found that as a participant's interest towards a task increased, their willingness to choose higher effort options also increased. In contrast, higher interest was associated with lower feelings of fatigue. Such a study shows that interest has tangential effects on effort and fatigue. Due to such findings, it is typically viewed that fatigue is neither necessary nor sufficient to explain effort effects (Wright & Pantaleo, 2013).

While some researchers hypothesised that fatigue interacts with motivation to indirectly regulate effort expenditure (Boksem et al., 2006), it is more commonly viewed that fatigue regulates the 'cost' of effort, reducing the subjective value (SV) of a reward as it increases (Iodice et al., 2017; Lopez-Gamundi & Wardle, 2018). Therefore, the estimated value of to task engagement reduces as fatigue increases, making it less worthwhile for the individual to continue with such effortful behaviour. When applying this to the scenario of the marathon runner, we can see that the runner must be sufficiently motivated by the payoff associated with task engagement to offset rising fatigue costs.

Task Difficulty

Task difficulty is often viewed as a strong determinant of effort (Gendolla et al., 2012; Kahneman, 1973). A close coupling between task difficulty and effort is supported by the observation that high cognitive effort strategies typically accompany high performance, with low-effort strategies typically leading to low performance. For example, being able to respond correctly when considering many variables may depend on the decision-makers' use of more effortful and higher-quality strategies (Payne et al., 1988). In the cognitive energetic model (Kahneman, 1973) it is assumed that behaviour is driven by a performance-cost trade-off, with the costs being subjective effort and physiological costs. Support for this comes from studies such as the one by Sperandio (1978), who found that air traffic controllers would adopt a lower performing more routinised work pattern when faced with high workload level beyond their typical comfortable workload. In sum, performance can be maintained under increased task difficulty at the expense of effort and recruitment of further resources, or lowered to reduce effort costs.

While many studies show that effort willingness decreases as task difficulty increases (Kramer et al., 2021; Strauss, et al., 2016; Westbrook & Braver, 2013), suggesting that effort reduces in response to declining performance, as with attention and fatigue, the relationship between effort and task difficulty is not always monotonic. For example, Westbrook and Braver (2015) point out that data-limited tasks (Norman & Bobrow, 1975), such as reading visually degraded words, may be difficult but not necessarily made easier by increased effort. Instead, a close but separate relationship between task difficulty and effort is reflected in the Motivation Intensity Theory (MIT; Brehm & Self, 1989), a long-standing theoretical framework of resource mobilisation, where effort is considered to be determined by the difficulty of the behaviour required to reach a goal, as well as success importance. In the MIT, the purpose of effort is to produce instrumental behaviour (otherwise referred to as motivation intensity). To explain why effort is not simply proportional to needs or outcome value, Brehm explains that effort is also mediated by success importance (otherwise known as potential motivation), and task difficulty, which both factor into the evaluation of maximum justified effort. Therefore, a core prediction of the MIT on the relationship between effort and task difficulty is that effort is in direct proportion to task difficulty, given that success is possible, and the required effort is also justified by success importance (Brehm et al. 1983). Such a conceptualisation allows for the relationship to be non-monotonic, whereby effort may increase with the difficulty of a task to a point, until a maximum tolerable difficulty is reached, at which point effort sharply drops.

In the MIT, task difficulty is a variable that determines effort allocation, with effort being the driver of behaviour. Recently, models building on Decision Theory (Slovic et al., 1977) that stipulate behaviour to be the product of an individual's unique cost/benefit calculations of potential control options, also situate task difficulty and effort as components of decision-making. Whereas MIT is concerned with the broad motivational determinants of effort, one influential model that formally describes the relationship between task difficulty and effort is the Expected Value of Control Model (EVC; Shenhav et al., 2013), which posits that an individual selects behaviour based on that associated with the highest expected value, accounting for costs and benefits associated with task engagement. The expected value of each task is hypothesised to be determined by motivational factors, namely performance efficacy (perceived likelihood of success), reward efficacy (the likelihood that high performance will lead to high reward), reward, and the effort costs of exerting cognitive control. Therefore, unlike the MIT, both task difficulty and effort are variables in the decision-making process that guides behaviour, through cognitive control allocation. Specifically, task difficulty is conceptualised to reduce the perceived benefit of a task, and effort to influence the cost.

According to the EVC, the amount of resources an individual allocates to a task is in-part dependent on the task difficulty of the candidate tasks on offer. This is because greater task difficulty both lowers likelihood of a good performance and increases effort costs. This means that if the candidate task on offer is new to the individual, or the difficulty is unknown, control allocation depends on estimations of task difficulty. In such cases where difficulty is estimated, the EVC predicts that a person would allocate their control up to the point that the actual task difficulty during task engagement matches initial expectations of task difficulty. In the case where the difficulty remains unknown even during task engagement, then the amount of control invested will stay corresponding to their original estimations. In both cases, it could be that the individual chooses to not engage at all, if their initial estimation of task difficulty seems intolerable. In the case when task difficulty can be accurately predicted, the EVC predicts that participants would choose the option with the lowest expected task difficulty, given reward being equal. This is a far more fine-grained explanation of how effort and task difficulty fit into value judgements compared to the MIT, and allows researchers to more confidently simulate and predict cognitive control allocation.

Risk

Risk-based decisions are typically those where an individual must account for the likelihood of each option paying off (also referred to as probability-based decision-making). Both effort and risk impact an individual's estimation as to the value of reward similarly to other costs, such as delay (Pre´vost et al., 2010; Richards et al., 1997; St Onge & Floresco, 2010). For example, Rachlin (1993) show that when decreasing the probability of a reward i.e., increasing the risk of no reward, outcomes lose some of their value. In the case of effort, the value of a reward has been shown to reduce as a function of increasing effort (Westbrook et al., 2013). One argument is that effort devalues reward as it is often associated with more difficult tasks. Therefore, the devaluation of reward due to effort reflects an anticipated reduction in the probability of successful task completion, i.e., increased risk.

Despite such reasoning, behavioural research from the effort-based decision-making literature has shown that even when controlling for the probability of reward, by having participants informed that their reward is not based on performance, but rather on their maintenance of effort, the value of a reward is discounted as the effort required to obtain it increases (Westbrook et al., 2013). Additionally, in a study directly assessing the relationship between probability (i.e., risk) and effort across three cost (easy, medium and large cost) and 2 reward (low and high) levels within-subjects, Białaszeket al. (2019) showed that participants discounted the value of smaller reward more steeply than higher rewards when making effort-based decisions, but that the opposite pattern was the case for probability-based discounting, whereby the reward was either certain or, 98%, 45% or 3% likely. Such findings are in line with related research showing contrasting patterns of magnitude discounting between effort-based (Ostaszewski et al., 2013) and probability-based (Green et al., 1999; Myerson, et al., 2011) discounting. Białaszek et al. (2019) also found significant moderate positive correlations (.54 - .59) between the area-under-curve, another approach to measuring discounting (Myerson et al., 2001), for different amount conditions within the same discounting type (e.g., probability low and high reward, $r = .55$). Other correlations across different discounting conditions were lower ($r < .23$), implying greater similarity within types of discounting than between types. Finally, using a factor analysis of indifference points, they identified a solution whereby one factor containing effort explained 6% of the variance composed of their effort conditions. Two other factors representing different probability discounting conditions also explained a further 8% and 5% respectively. Such results show high consistency in the loading of effort and risk on separate factors as well as clear discriminability between factors. A further factor analysis of the area-under-curve measure also divided probability of reward and effort.

Further support for a dissociation between risk and effort comes from distinct neural patterns between discounting models based on risk and effort. For example, Burke at al. (2013) found contrasting fMRI activation between representations of costs related to risk and physical effort respectively. Specifically, they found risk to be associated with increased activation in the anterior insula, with effort being in the supplementary motor area. Other studies using rats show that lesions to the anterior cingulate cortex, a key region thought to be involved in effort-based decisions, does not impact probability-based discounting (Schweimer & Hauber, 2005), but leads to more choices of low effort options (Walton et al., 2003). In summary, the anterior cingulate cortex, nucleus accumbens core and shell and ventral pallidum are typically implicated during effort-based decisions, whereas pre-limbic cortex, nucleus accumbens shell subregion, baso-lateral amygdala and ventral tegmental area are particularly active during probability-based decisions (Bailey et al., 2016).

The existing evidence suggests that both effort and risk represent distinct cost factors to discounting (Bailey et al., 2016; Białaszek et al., 2017; Białaszek et al., 2019). What remains to be understood is exactly how these costs relate, or are perhaps integrated (Białaszek et al., 2019, Shenhav, et al., 2021). One possibility is that effort costs are weighted by the extent to which effort is likely to lead to good performance (i.e., performance efficacy), and thus positive outcomes (Shenhav et al., 2021). Therefore, if greater effort has little bearing on performance, then the cost is unlikely to be deemed worthwhile by the individual. It may also be that the payoff of effort is weighted by the likelihood for which good performance leads to rewarding outcomes (i.e., reward efficacy). Therefore, if reward has little to do with performance, then the estimated payoff of effort is likely to be reduced. Exactly how an individual assesses risk in terms of performance and reward requires further formal investigation, though regardless, effort is viewed as being separable.

Grit

Grit is conceptualised as a willingness to sustain effort over time (Duckworth et al., 2007). Unsurprisingly, studies have shown that grittier students are more likely to achieve academic success and perform higher on exams compared to those who are less gritty (Lee & Sohn, 2017; Pate et al., 2017). It is hypothesised that 'gritty' students are more engaged in their studies (Datu et al., 2018) and spend more time studying, i.e., put in more effort (Cross, 2013). This mirrors findings from the effort literature showing that effort expenditure can act as a predictor of academic achievement (De Jong, 2010).

Despite such findings, recent studies looking at the usefulness of grit as a predictor of university academic achievement or course success find prior academic performance, rather than grit, to be predictive of current academic performance (Bazelais et al., 2016; Palisoc et al., 2017). One possible explanation is that grit is an indirect predictor of success, and in fact mediates effort put in, which in turn influences success. In this way, being 'gritty' means that you are more likely to exert effort and time into studies, which in turn has an impact on success. This perhaps explains why in the study by Palisoc et al. (2017), grit was found to predict post-graduate training attainment, but not other success outcomes. In a study directly assessing the relationship between grit, effort and academic outcomes, Hagger and Hamilton (2019) measured grit perseverance (grit-effort), consistency of interest (grit-interest), self-discipline and effort for out-of-school learning activities from 117 school students. Effort on optional out of school learning activities was measured using 5-items set by the pupil's science teachers. Bayesian path analysis was then run to assess which factors would predict final grades collected at the end of the semester. The three predictors (grit-effort, grit-interest, and self-discipline) were found to correlate. They also found direct effects of grit-effort on effort, self-discipline to effort, self-discipline to science grades and effort to science grades. Importantly, they found indirect effects of grit-effort to effort and then to grades, as well as for self-discipline to effort and then to grades. Therefore, the effect of grit-effort was mediated by effort. This may explain why grit-effort is predictive of success e.g., academic achievement (Weisskirch, 2018) and self-regulated learning (Wolters & Hussain, 2015), over and above overall grit and the consistency of interest subscale. In line with this, Mason (2018), estimates perseverance of effort to be three times as predictive of academic achievement than consistency of interest.

Such a finding is in line with Duckworth and Gross' (2014) proposal that the process through which gritty individuals pursue long-term goals is through consistent goal-directed efforts. Therefore, grit is reflective of an individual's propensity to exert effort over time, whereas effort is more closely related to the actual cognitive capacity allocated to learning and task performance (De Jong, 2010). The finding that high grit-effort students' effort on out of school activities contributes to their academic attainment of science in the long-term indicates that the relationship between grit and positive outcomes is, at least in part, attributable to the fact that those with higher grit were particularly more willing to exert greater effort towards out of school learning activities than their less gritty peers.

Need for Cognition

NFC is defined as a trait disposition to engage with demanding activities in daily life, as measured with the Need for Cognition Scale (Cacioppo & Petty, 1982). NFC explains why some people seem to enjoy exerting effort for its own sake, whereas others avoid effort exertion whenever possible. A leading hypothesis is that those high in NFC assign greater value to effort, and thus require less reward to exert it, and seek out effort rather than avoid it (Sandra & Otto, 2018; Westbrook et al., 2013). Similarly to effort, NFC predicts higher academic achievement and performance for a range of memory, problem solving, and maths tasks (Cacioppo et al., 1996). NFC has also been shown to predict the amount of money an individual will forgo to avoid completing a cognitively demanding activity (Westbrook & Braver, 2015).

While closely related, the possibility of a task becoming boring, regardless of trait NFC, suggests that effort is not only trait, but also state dependent. Therefore, rather than making potentially inaccurate assumptions relating to an individual's willingness to engage with a task based on their trait-like NFC, preferences for task engagement should also account for state-dependent aspects. In a study examining how individuals vary in how they value cognitive effort for reward, Sandra and Otto (2018) found that low NFC predicts a larger increase in cognitive effort expenditure in response to monetary reward incentives compared to those with greater NFC; who were less responsive to reward incentives. It was also found that participants with low NFC exhibited a reward-induced switch cost reduction, whereas the high NFC participants exhibited the opposite. Therefore, large reward incentives had contrasting effects on those with high and low NFC, such that those with low NFC increased effort exerted, while surprisingly high NFC participants decreased their effort. This may be because individuals high in NFC, who are more willing to exert effort, place intrinsic value on the exertion of effort, or perhaps do not treat it as costly, making it possible for their effort to reduce despite increasing extrinsic reward. Such results further highlight how the SV an individual places on effort for reward is influenced by an interplay between dispositional factors such as NFC, as well as specific aspects of the task in question. More research is needed to understand the exact nature of the relationship between effort and NFC, though the current evidence suggests that effort reflects both trait-like NFC as well as state-like task-specific preference. Recent research looking at the role of experience (e.g., training) on effort (Chong et al., 2018) may also help to further elucidate how trait-like aspects such as NFC and state-like aspects concurrently influence decisions to exert effort.

Cognitive Control

Many studies investigating effort consider it in relation to the allocation of cognitive control (Westbrook & Braver, 2015). Cognitive control is defined as the set of "superordinate functions that encode and maintain a representation of the current task" (Botvinick & Braver, 2015). In other words, cognitive control is the collection of mechanisms that bias information processing in accordance with a task goal, and away from distractors or overriding prepotent responses (Cohen et al., 1990). Therefore, cognitive control is responsible for overriding more automatic processes to engage in deliberative information processing (Embrey et al., 2023). Typically, control is understood in terms of direction and intensity. Direction refers to the goal towards which the control is being exerted by subordinate systems. Intensity refers to the rigour or strength of its top-down influence on those systems (Shenhav et al., 2013).

Like effort, Embrey et al (2023) point out that allocating cognitive control is difficult and necessary for performance in a range of tasks. Both effort and cognitive control theories are also built upon the principle of optimisation, which is that individuals should seek to find the best solution for an objective function and set of constraints (Shenhav et al., 2013; Kurzban et al., 2013). Moreover, the core objective of cognitive control allocation is to maximise reward (Lieder et al., 2018; Boureau et al., 2015; Shenhav et al., 2013). Therefore, people adjust the direction and intensity of their cognitive control to maximise the expected payoff (Ritz, et al., 2022).

One possibility for how effort and cognitive control relate is that mental effort is the sole determinant of cognitive control. For example, Székely and Michael (2021) propose that mental effort is a measure of the extent to which cognitive control inhibits and/or modifies default procedures to ensure that the procedures that are implemented are specifically tailored to the task context. Such an interpretation could be taken as saying that effort is monolithic. However, most perspectives explicitly distinguish between effort and cognitive control, where effort is primarily involved in decision-making, whereas cognitive control is also implicated in a range of other higher-order cognitive functions, such as working memory and problem solving. This is highlighted in the Dual Mechanisms of Control framework (Braver, 2012), in which two modes of cognitive control are described, the first of which is proactive task set preparation and maintenance. This mode is effortful but also likely performance-enhancing and involves the sustainment and maintenance of goal-relevant information to optimise cognitive performance. An example of this could be a student preparing to write their thesis: they establish a plan, allocate writing time, and create a productive working from home set-up. The other is a less effortful reactive mode of control whereby attention is only mobilised as a 'late correction' mechanism in response to interference. An example of this could be seeing that the cycle path you use to take to work in the morning is blocked with roadworks and having to plan an alternate route in the moment. It is important to note that the distinction between these two modes is a relative one, whereby a cognitive process is considered more automatic (i.e., less effortful), the less it interferes with other cognitive processes (Botvinick et al., 2001). Regardless, the point remains that effort and cognitive control are conceptually distinct.

One formal explanation for how effort and cognitive control relate comes from Shenhav et al. (2017), who define effort as what mediates between the characteristics of a target task and the individual's ability to complete the task, and the fidelity of the task performed. In their EVC model, Shenhav and colleagues describe behaviour, at least for cognitive tasks, to be driven by cognitive control allocation. Therefore, they position cognitive control as the force through which individuals perform cognitive tasks, whereby the intensity of motivation is relative to the amount of cognitive control allocated to a task. Like other models, the allocation of cognitive control is hypothesised to be determined by whichever option is associated with the highest expected value. They argue that this value is calculated in terms of identity (what task to attend to) and intensity (how much control to allocate), and that the individual selects the option with the highest yield, i.e., the highest benefit to cost ratio. From this perspective, effort is viewed as one of the costs (along with time and risk), and the benefit is the payoff associated with the effort exertion. Therefore, rather than being a characteristic of a control type, as in the Dual Mechanism of Control model (Braver, 2012), effort is conceptualised as a cost associated with completing a task that helps to solve the decision of how to configure cognitive control (Ritz et al., 2022).

A key strength of the EVC is that it integrates a range of empirical findings related to effort by accounting for the dissociation between capacity (intrinsic limitations) and willingness (motivational factors) to exert cognitive control. In taking a computational approach to decision-making, the EVC can be used to derive quantitative and rigorous predictions of effort-based decisions. For example, using the EVC, differences in cognitive control allocation across different tasks within an individual can be better understood (e.g., for cognitive versus physical tasks). This is because the EVC emphasises the importance of an individual's priors, such as their ability (Shenhav et al., 2021), that may influence the subjective interpretation of costs and benefits associated with control allocation. In addition, the EVC offers a novel perspective on how aspects such as affect influence motivation to exert effort (Grahek et al., 2020), as it constrains the possible routes for which they can influence cognitive control (I.e., by biasing the estimation of outcomes, perceived task difficulty, and costs associated with candidate tasks). A further advantage of the EVC is that it can be used to understand psychiatric disorders, in terms of how individual differences in decision-making processes lead to deficits in task performance. As highlighted by Grahek et al. (2019), the EVC is a computationally explicit model of cognitive control allocation that allows researchers to look at ways in which the expected value of control may be influenced by different disorders (e.g., depression), resulting in allocating cognitive control with either different identity or reduced intensity (Shenhav et al., 2013). They argue that the EVC allows researchers to assess more accurately how disorders influence perceived efficacy, the value of outcomes and the effort required to obtain them, which ultimately underpin the decision-making process about control allocation. Finally, the EVC model can be used to quantify the relationship between different variables present in leading models of motivation, such as the MIT (Brehm & Self, 1989). For example, while perceived difficulty is conceptualised as an important variable in the MIT, the EVC allows for the more precise predictions as to the impact of changes to the task or the individual on behaviour. In sum, the EVC provides the most finely grained computational model underlying motivated cognitive control.

Despite the strengths of the EVC, it is yet to be used to address some outstanding questions relating to how effort and cognitive control exactly relate. For example, does cognitive control guide physical behaviour, and if so, does effort also mediate engagement in the same way? Additionally, if effort is conceptualised as a mediator of cognitive control, does that mean that there cannot be effort without cognitive control? Addressing these questions would be particularly beneficial in understanding individual's effort willingness in their daily life and may also be relevant in understanding other constructs for which cognitive control does not seem to drive engagement, such as flow.

Motivation

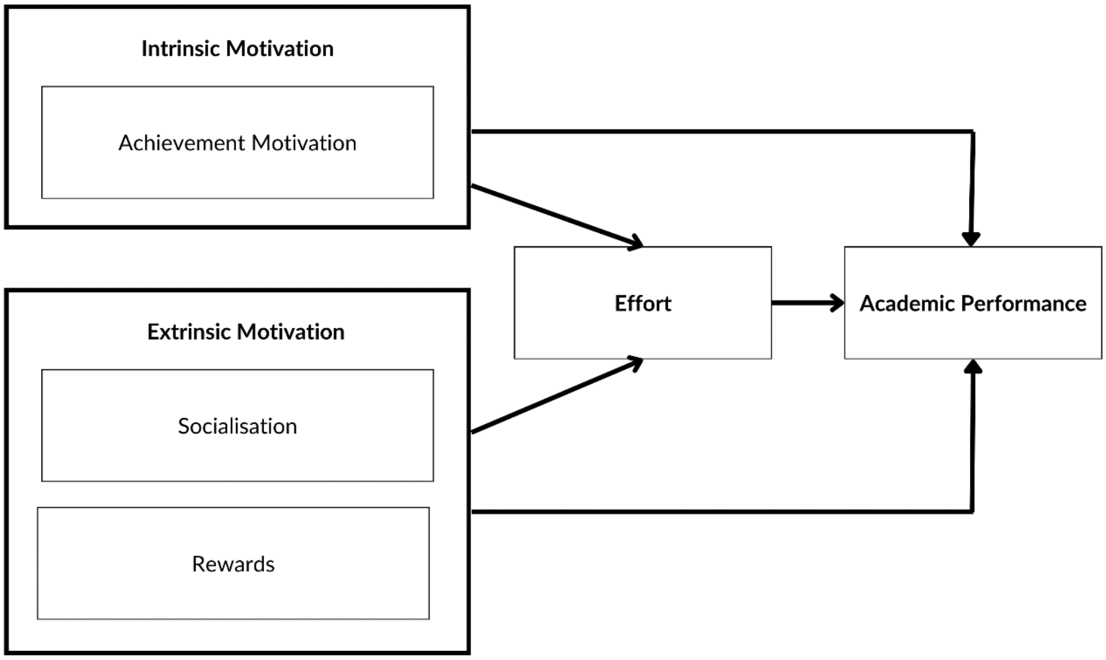
Motivation is typically defined in terms of the behaviourally relevant processes that enable an organism to regulate its external and/or internal environments (Ryan & Deci, 2000) and control the probability, proximity, and availability of stimuli (Salamone et al., 2016). More specifically, motivation is thought to determine the direction and energization of behaviour to attain a goal, while accounting for the cost of doing so (Elliot & Fryer, 2008; Holland, 1999; Murray et al., 2006). Researchers typically recognise two major types of motivation, intrinsic or extrinsic. Intrinsic motivation refers to 'doing something for its own sake', whereas extrinsic motivation refers to the pursuit of an instrumental goal (Reiss, 2012). While referring to them independently can be useful in understanding certain motivational processes, modern dualistic accounts typically posit that actions are often best described as being motivated by a combination of intrinsic and extrinsic factors (Rigby et al., 1992). For example, Müller and Louw (2004) assert that extrinsic factors such as supportive social environments can counteract negative factors and foster intrinsic motivation. Similarly, another study by Dass-Brailsford (2005) found that while motivation can be reduced by a stressful home and family environment, students with high intrinsic motivation for studying can counteract these negative familial factors.

Like effort, high motivation has also been shown to have both clinical and non-clinical relevance, from explaining variance in academic and workplace performance (Fraser & Killen, 2005; Robescu & Lancu, 2016; Stanca, 2006), to improving effectiveness of psychosocial treatments of schizophrenia (Medalia & Saperstein, 2011). Motivational incentives (e.g., monetary reward) can also counteract fatigue, demonstrating that effort is at least partly volitional and tied to motivation (Boksem & Tops, 2008). Furthermore, increasing motivation has also been shown to maintain willingness to exert self-control over extended periods of exertion (McVay & Kane, 2010). Due to the close coupling between effort and motivation, performance on effortful tasks such as hand grip tasks have often been used as proxy measures of motivation (Cléry-Melin et al., 2011; Schmidt et al., 2012a).

However, not distinguishing between effort and motivation makes it difficult to explain why individuals can be motivated, or not, to put in both high and low effort (Inzlicht et al., 2018; Shenhav et al., 2017). For example, an individual could be motivated to exert effort, such as during an exam, but then at other times be motivated to not exert effort, such as before sleep. In addition, it seems intuitive that it is effort, not motivation, that is ultimately exerted during task engagement e.g., when gripping a hand grip dynamometer. Based on this, one integrated view is that effort is a proxy of motivation, such that motivation impacts behaviour indirectly through effort (Goodman et al., 2011; Figure 1).

Figure 1

An Integrated Model Proposed by Goodman et al. (2011) of How Effort May Mediate the Relationship Between Motivation and Performance. Permission was Granted for Use of This Figure by the South African Journal of Psychology



In a study investigating the potential role of effort in mediating the relationship between motivation and performance, Goodman et al. (2011) compared self-reported motivation to the amount of time spent on assignments and GPA. Effort was found to be a partial mediator of the relationship between motivation and academic performance. Furthermore, they went on to show using multiple regression analyses that intrinsic motivation was the strongest predictor, followed by effort, with extrinsic motivation not explaining any unique variance. In line with this, another study by Foussias et al. (2015) found effort to explain 15% of the variance in cognitive performance of patients with schizophrenia or schizoaffective disorder, and that it partly mediated the relationship between motivation and cognitive performance. Another study by Vasalampi et al. (2014) finds self-reported effort to be predicted by both personality traits, particularly conscientiousness and agreeableness, as well as autonomous motivation. All of the above findings support the notion that effort is a mediator between motivation and performance.

Another theory of motivation that explicitly separates effort and motivation is the self-determination theory (Deci & Ryan, 1985; Deci & Ryan, 2000), that posits that individuals have their own reasons for specific goals, and that these have implications for the type, quality, and quantity of effort that they are willing to invest to meet those goals (Ryan & Deci, 2000). Specifically, studies show that those whose goals are autonomously motivated, i.e., those pursued as an expression of personal choice (Sheldon & Elliot, 1999), invest more sustained effort into achieving those goals but also the quality of their effort is higher (Sheldon, 2002; Trautwein et al., 2006). This contrasts with goals motivated by control, i.e., because a person feels controlled by external pressures or stimulated by factors such as guilt or anxiety (Deci & Ryan, 1985; Ryan & Deci, 2000; Sheldon & Kasser, 1998). For example, Turban et al., (2007) show that perceived locus of causality with regards to school courses strongly mediates effort. It is hypothesised that controlled motivation does not satisfy an individual's psychological needs, promoting disengagement when confronted with obstacles (Deci & Ryan, 2000; Sheldon & Elliot, 1999).

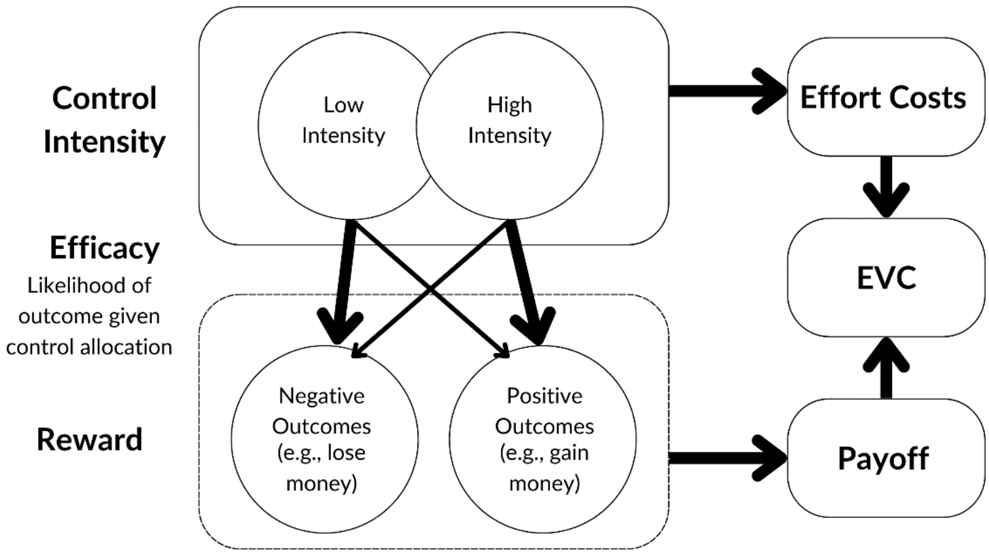
Another theory conceptualising effort as an outcome of motivation is the MIT discussed previously (Brehm & Self, 1989), which is focused on understanding which factors and mechanisms underlie the investment of resources to carry out behaviour. As a brief reminder, the MIT posits that motivation includes the maximal amount of effort an individual would be willing to exert in principle (potential motivation), as well as the amount of effort exerted in the pursuit of a goal (motivation intensity; Gendolla & Wright, 2009). The above definition aimed to explain behaviour for a range of tasks, both physical and cognitive, meaning that the exact nature of the resources could be physiological, psychological, or functional in nature (Silvestrini & Gendolla, 2019). Silvestrini et al. (2023) argue that while effort and MIT literatures both seek to explain mechanisms underlying motivation to engage in effortful behaviour, MIT is concerned with the broad motivational determinants of effort mobilisation in goal pursuit. Instead, effort is conceptualised an output of motivational processes that enable the execution of behaviour, whereby its function is to sustain activity necessary for goal attainment.

Rather than as an outcome of motivational processes, current formalisations of how effort and motivation relate position effort as a subcomponent of motivation. For example, Pessiglione et al. (2018) conceptualise motivation as a mechanism of the brain that adjusts the direction and intensity of behaviour, such to reduce the delay or increase the probability of goal attainment. Therefore, effort is conceptualised as being a cost involved by the behaviour, that is offset by potential reward or avoidance of punishment associated with reaching the goal.

This perspective is echoed by the EVC discussed previously (Shenhav et al., 2013, Shenhav et al., 2021), which is a model of motivation focussed on the interaction between motivation and cognitive control (Botvinick & Braver, 2015; Shenhav et al., 2013, 2017). In this model, motivation is viewed as a key determinant of behaviour, which itself is in-part determined by effort costs. Like the model from Pessiglione et al. (2018), the EVC argues that behaviour determined on two dimensions, the identity and intensity of the engagement. In addition, this model explicitly proposes that expected outcomes are weighted by the extent to which effort matters for goal attainment, both in terms of leading to good performance, and positive outcomes (Musslick et al., 2015, 2019). Therefore, an individual is likely to be willing to exert higher cognitive control for a task where how much control they engage has a large bearing on performance, and that is certain to lead to a payoff, compared to a task with low control and performance efficacy. They are also predicted to choose a task with lower effort costs, compared to an equally rewarding task with higher effort costs. In this way, effort is an important variable of motivation, and reflects a cost associated with a task, alongside other costs such as time and risk, that are offset against the benefits of control (Figure 2; Frömer et al., 2021).

Figure 2

*Outline of the Expected Value of Control Theory (EVC), A Motivational Theory in Which Effort is Positioned as a Mediator of Perceived Task Value, Which In-Turn Determines the Allocation of Cognitive Control (*Frömer et al., 2021*). The Above Figure Shows EVC Calculation in Terms of Intensity, Whereby Control Intensity If Chosen to Optimise the Trade-Off Between Effort Costs and Payoff. This is Also Hypothesised to Occur for Identity (I.E., What to Attend to), Whereby the Task That Leads to the Maximal Expected Value is Selected. The Above Figure Also Only Shows Performance Efficacy, which is the Extent to Which Increased Control Leads to Increased Positive Outcomes. The EVC Also Includes Performance Efficacy, Which Is the Likelihood That High Control Leads to High Performance, Which in Turn is Discounted by Reward Efficacy.*



Pain

Pain is typically defined as a distressing experience associated with actual or potential tissue damage (Williams & Craig, 2016). Like effort, pain is thought to have a cognitive component, with studies showing the impact of pain on loss aversion (DeWall et al., 2015), and risk-based decisions and self-reported effort (Barnhart et al., 2019). Traditionally, both effort and pain are thought to play functional roles, acting as 'stop signals', promoting conservation and the optimisation of limited resources. This is because, like effort, pain has been considered in the context of decision-making to be a cost that can be overcome to a certain extent, in the pursuit of greater rewards. For example, in a within-subjects study assessing relative cost of effort and pain, Vogel et al (2020), asked participants to choose between completing the N-back working memory task and receiving pain via a thermal pad stimulus using the COG-ED design. They found that eventually participants would choose to experience pain rather than complete a more effortful working memory task, demonstrating the shared aversive characteristic between the two. Vogel and colleagues also found that participants were slower to choose both high effort and higher pain options, indicating that people may be reluctant to choose the more costly option, regardless of whether that cost is effort or pain.

While this study supports the notion of both effort and pain and being costs that are considered during decision-making, asking participants to simultaneously consider both effort and pain makes it difficult to unpack whether choices were made particularly due to effort willingness or pain tolerance. Therefore, to what extent is participant choice influenced by how the participant perceive the cost of effort compared to pain? To explore this, in an additional exploratory analysis Vogel compared NFC and pain catastrophizing scores, the severity to which participants experience pain, in explaining effort/pain choice. While a moderating effect of NFC on the interaction between pain and effort offer was found, as well as a moderating effect of pain score on the influence of effort level on choice, NFC and pain scores were not found to significantly relate. To find that NFC could predict choices between effort and pain, is in line with studies showing that effort willingness and NFC can be predictive of one another (Mækelæ et al., 2023; Westbrook & Braver, 2015). However, to find that NFC and pain did not directly relate suggests that effort willingness and pain tolerance are two distinct but related components that separately influence choice behaviour.

Rather than considering choices between one or the other, one way to compare the two is to ask the question of ‘how do effort choices relate to a separate measure of pain tolerance?’. Therefore, could pain tolerance be predicted by SV of effort and vice versa? This is an exploratory question that is addressed in Study 1, where we correlate pain tolerance as measured using a cold pressor to SV for a range of effortful tasks as measured using the Effort Discounting Task (EDT) paradigm to be discussed in Chapter Two. If we find that the two correlate, then it would support the idea of overlapping systems for effort and pain willingness, particularly if that were to be the case for all effort tasks. If, however, they are not correlated, then it would support the notion that both effort and pain are independent aspects of decision making.

Intelligence

Intelligence can generally be defined as the ability to learn from experience and to adapt to, shape, and select environments (Sternberg, 2012). This ability is thought to be the product of a combination of genetic and environmental influences, whereby you may be born with certain predispositions for intelligence, but also put forth effort into developing your intelligence further throughout the course of your life (Eysenck, 2018, Chapter 3).

Studies have found that general intelligence, as measured using the Shipley-2 Scale which involves a general IQ test involving vocabulary questions, abstraction, and block patterns (Shipley, 2009), to relate to neither cognitive nor physical effort willingness (Lopez-Gamundi & Wardle, 2018). Contrary to this, the same study found working memory ability to relate to effort, such that greater ability leads to greater effort for the cognitive, but not physical version. This is supported by another study published in the same year conducted by Sandra and Otto (2018), who tested whether those low in cognitive capacity perceive the costs to be greater than someone with a comparatively higher cognitive capacity. They utilised the Stroop test, where reduced switch reaction time (RT) costs were used as a measure of greater cognitive effort investment, and reduced Stroop RT used as a measure of greater executive function capacity. They found reward driven modulations of effort to be more prevalent in people with lower executive functions, which they argue to be due to the increased costs being offset by changes in reward. This is compared to participants with high executive function, who did not increase effort as a function of reward to the same degree.

Taken together, these studies suggest that aspects such as intelligence and working memory can influence effort-based decisions, but only insofar as they are relevant to the task in question. In the study by Lopez-Gamundi and Wardle (2018), the cognitive version of the task was a working memory task, and the physical version was button pressing. Therefore, it is unsurprising that working memory ability would only be relevance when making an effort-based decision for which working memory is relevant when estimating SV. This also explains why intelligence has failed to explain effort choice patterns, as it is presumably not a relevant enough factor when an individual is deciding whether to complete a Stroop, or button press task.

In Study 1, we test if intelligence as measured by Raven's Advanced Progressive Matrices (APM, Raven & Court, 1998) relates to effort willingness. In the Raven's APM, respondents identify the pattern or rule that governs the arrangement of 3x3 geometric shapes shown from options provided. The test is considered a measure of fluid intelligence, which is a specific aspect of general intelligence which relates to the ability to think logically and solve problems independent of acquired knowledge, focusing on pattern recognition and abstract reasoning (Cattell, 1963). We do this because we want to test if a null finding is found once again when using a different intelligence measure, across a new range of effort tasks (auditory discrimination, working memory, weighted backpack). It may be that fluid intelligence is more related to effort-based decisions, given its relevance during novel situations (Unsworth & Engle, 2005), which will be the case with the specific lab tasks chosen for Study 1. However, given the previous null findings, it remains unclear whether effort and intelligence meaningfully relate.

Anxiety

Anxiety is typically defined as a psychological state characterised by excessive worry, apprehension, and nervousness, that can occur in response to perceived or actual threat (APA, 2013). Understanding the relationship between effort and anxiety is relevant in understanding the mechanisms underlying anxiety disorders and other related conditions for which anxiety is commonly associated, such as depression and obsessive-compulsive disorder, amongst others (Kessler, et al., 2005). Such disorders are often detrimental to the life of those effective, with anxiety preventing engagement in activities that may otherwise provide individuals with anxiety reduction or positive reinforcement.

In a review of how anxiety influences decision-making processes, Hartley and Phelps (2012) highlight that particularly during effortful tasks, individuals with greater anxiety are more likely to display task avoidance. They posit that such avoidance may reflect a maladaptive coping strategy, whereby those with higher anxiety seek to minimise their exposure to potentially stress inducing situations. This is thought to lead to those with anxiety overestimating the cost of effort required, and/or undervaluing potential rewards. Anxiety has also been hypothesised to trigger automatic avoidance behaviours. Geurts et al (2013) examine the role of Pavlovian responses in effort-based decisions and show that anxiety may lead to more 'model-free' strategies, which are habitual responses which can be viewed as more reliable in response to uncertainty. Such a finding suggests that anxiety can trigger automatic avoidance behaviours, beyond anxiety/threat response to avoidance of effortful tasks in general.

From a neurobiological perspective, Hartley and colleagues point to the disrupted functioning of brain regions such as the prefrontal cortex and striatum, that are implicated in the evaluation of effort and reward. This is echoed by Chong et al (2016), who suggest that anxiety may modulate brain circuits involved in the evaluation of effort and reward, resulting in anxiety biases away from effortful activities. Taken together, these studies suggest that anxiety may lead to effort avoidance, driven by cognitive biases and automatic anxiety-related responses, and neurobiological disruptions. The studies highlight the important role that anxiety may play in effort-based decisions, which may underly many functioning issues seen in anxiety disorders.

Despite the recent emergence of a range of effort measures, studies are yet to assess whether anxiety levels present in the general population relate to effort. Therefore, could anxiety be a relevant contributor to people's willingness to exert effort? This is a question that is addressed in Study 1, where we relate anxiety symptomology to effort willingness using a prominent effort measure (Westbrook et al., 2013) in a general non-clinical sample.

To What Extent is Effort Aversive and Why?

Another division in the effort literature relates to the extent to which effort is aversive. Traditionally, effort researchers have assumed effort to be aversive due to studies showing its apparent cost. However, researchers have more recently found evidence suggesting that effort may be a value-add, opening the possibility of effort being appetitive. The aim of this second section is to critically consider both possibilities in turn, before exploring studies that suggest the subjective feeling of effort may range from anywhere between aversive and appetitive, depending on the tasks perceived value.

Effort is Costly

As goal-directed behaviour is constrained by cognitive capacity limitations, e.g., working memory capacity, one key notion is that decisions to engage in a task should be dictated, at least in part, by the costs and benefits associated with task engagement. Traditionally, effort has been viewed as a cost, not only due to its aversive phenomenology (Kurzban, 2016), but also because of a multitude of experiments from various disciplines, particularly psychology and psychophysiology, showing effort aversion across a range of behavioural tasks. For example, studies using the Demand Selection Task (DST; Kool et al., 2010), during which participants repeatedly choose between two decks of cards associated with different demand levels of a rule switching task, show how participants consistently demonstrate a preference for options associated with lesser demand, compared to options associated with greater demand, given no reward incentive for either case. Such finding imply that the increased effort required to switch from one decision rule to another during a higher demand level carries a greater intrinsic cost than an alternative choice associated with lesser rule switching. Effort being costly also explains why, given the choice between two activities of equal benefit, participants tend to choose the one that requires the least effort for the most reward (Hull, 1943; Patzelt et al., 2019, Westbrook & Braver, 2015). According to the effort discounting principle, this is because the SV of a reward is greater if it is comparatively easily obtained (Botvinick et al., 2009; Phillips et al., 2007; Rudebeck et al., 2006), similarly to how other motivational costs such as delay, and probability are thought to influence the value of reward (Green & Myerson, 2004).

Effort has shown to be costly for goal-oriented behaviour spanning both cognitive and physical domains. For cognitive efforts, studies have demonstrated that the SV of a reward varies as a function of the cognitive effort required (Białaszek et al., 2017; Massar et al., 2018; Westbrook et al., 2019). Similarly, it has been shown that the anticipated cost of physical effort devalues the SV of a reward that is contingent on its exertion (Białaszek et al., 2017; Klein-Flügge et al., 2015). Therefore, in both cases, participants choose the option with the highest SV, due to the lesser cost. The trade-off between the cost of effort and the benefit of reward is nicely demonstrated in a recent paper by Embrey et al. (2023), who show across three studies that more difficult tasks are generally avoided, and that participants are willing to forgo increased amounts of reward as the difficulty disparity between the two options grows larger. The authors argue this to reflect increased effort costs, rather than due to reduced perceived efficacy, as participants were informed prior to making effort-based choices that reward was not dependant on performance.

Studies also show that both cognitively and physically effortful tasks evoke similar facial electromyographic responses in muscles also associated with negative affect (von Boxtel & Jessurun, 1993; Dreisbach & Fischer, 2011). Specifically, facial Electromyography over the corrugator supercilii muscle is known to increase when an individual is angry or scared (Burrows et al., 2009), experiencing pain (Prkachin, 1992), viewing aversive stimuli (Larson et al., 2003), or making an error (Lindström et al., 2013). The same area has been related to self-reported effort for a two-choice serial reaction task using visual or auditory stimuli (van Boxtel & Jessurun, 1993), leg extensions (de Morree & Marcora, 2010) and a simple information processing task using two visual stimuli (Waterink & van Boxtel, 1994).

Such findings support the notion that effort is always costly to some extent, and so should subjectively devalue any rewarding outcomes that are contingent on it. Consequently, most researchers in social science have for many years considered people to be 'misers', who conserve their effort and allocate it wisely (Fiske & Taylor, 1991). This notion is in line with typical principles of resource mobilization, that state that individuals conserve effort by choosing the easiest path to goal attainment e.g., the principle of minimal effort (Tolman, 1932). Furthermore, many 'nudge' interventions (Thaler et al., 2014), such as putting healthier foods at eye level to promote better nutrition, rely on this assumption that people seek to minimise their effort expenditure. Likewise, 'channel factors', such as giving people a scheduled time and location to get a vaccination, provide a prescribed path to a goal, reducing effort costs (Lewin, 1947).

However, a preference for effort avoidance does not necessarily align with how people choose to allocate their efforts in daily life. For example, playing video games, completing a crossword puzzle and cooking your favourite meal can all be both effortful and phenomenologically enjoyable. Such activities vastly differ to those typically used to assess mental effort in the lab. With regards to effort and video games in particular, it is commonly observed that players typically choose difficulty levels to match their ability, rather than the lowest effort condition (Baranes, et al., 2014). Such findings explain why game developers invest significantly in fine tuning skill-based matchmaking algorithms to maximise engagement (Graepel & Herbrich, 2006), and suggests that effort may not always be costly. Such observations have led to the emergence of a new perspective on effort, one that positions effort not as a cost, but instead as a value-add.

Effort Adds Value

The perspective that demanding tasks can be appetitive, rather than aversive, is the premise of the Need for Cognition Scale (Cacioppo & Petty, 1982). In the case of effort, there are many notable exceptions where effort does not seem to carry a cost in which people enjoy and seek out opportunities to expend effort, such as when they deliberately go for a run or complete a crossword puzzle (Inzlicht et al., 2018; Shenhav et al., 2017). Therefore, it is important that theories can explain instances where effort seemingly carries little to no cost.

One argument is that effort exerted in the service of a goal does not necessarily need to be costly, and can contribute to an increased evaluation of its consequences i.e., prior effort can influence people's valuation of subsequent reward (Jurczyk et al., 2019). A study looking at the relationship between effort and the value of outcomes is the one by Norton et al. (2012), who investigated the notion of effort increasing the value of a product. In this study, consumers were asked to assemble IKEA boxes, fold origami, and build a Lego set. They found that labour led to participants perceiving their creations as of equal value to professionals, when the labour was associated with a successful outcome/completion of the task. The idea of effort increasing the value of reward is in line with studies showing greater appreciation for social groups that involve an effortful initiation. For example, being required to read embarrassing material before joining a group compared to not being asked has been shown to increase group liking (Aronson & Mills, 1959). Others show that conditioned reinforcers following high effort tasks are preferred. For example, Alessandri et al. (2008) showed that coloured rectangles presented prior to greater physical effort were more preferred compared to rectangles associated with lesser effort when later asked. This may explain why, compared to windfall gains, people have decreased willingness to spend money from earned gains (Arkes et al., 1994).

Neuro-imaging papers support the notion that effort can add value to outcomes. For example, Ma et al. (2014) showed that participants showed less negative evoked-related negativity, a proxy for greater motivational evaluation, in response to effort-related reward, compared to the same reward for less effort. They also found that amplitudes of P300, another marker for the motivational significance of stimuli (Nieuwenhuis et al., 2005), were more positive in response to rewarding compared to non-rewarding conditions, exclusively for high-effort conditions. Such findings have recently been replicated (Wang et al., 2017), and suggest that people value outcomes more when coupled with greater effort expenditure towards their receipt.

Another argument is that, in the same way that effort may be aversive because people acquire avoidant associations, people may also form positive associations, leading to not only the outcome of effort to be valued, but to effort itself becoming valued (Inzlicht et al., 2018; Shenhav et al., 2021; Sź ekely & Michael, 2020). Specifically, can behaviours acquire positive intrinsic value and become a rewarding in their own right if repeatedly paired with reward? The notion of effort becoming a secondary reinforcer in this way may explain the concept of 'flow', which is the positive state of immersion and enjoyment during effort exertion (Csikszentmihalyi & Larson, 2014). Such an effect may also relate to learned industriousness, which is when effort itself comes to predict reward as a secondary reinforcer when repeatedly paired with reward, thereby reducing its aversiveness (Eisenberger 1992). While many studies on learned industriousness can be considered largely correlational, with little direct evidence, the notion that effort itself can become rewarding is an interesting one worthy of further investigation.

When looking to test the idea of whether rewarding effort can increase its value, or perhaps reduce its cost, it is important to consider the distinction between intrinsic task motivation, and the intrinsic value of effort. This is because, rewarding effort is not necessarily expected to lead to people being more willing to work on previously incentivized task without extrinsic reward. Therefore, rewarding effort may not improve people's intrinsic motivation to complete a task, but may improve the intrinsic value of mental labour, such that participants begin to value it and seek it intrinsically on other unrelated tasks. Accordingly, it is important that effort seeking is assessed on a different transfer task so as to not undermine intrinsic task motivation with extrinsic reward.

One study that did just this was conducted by Clay et al. (2022), who in their first study asked participants to complete a working memory task (the n-back task), where rewards were either effort-contingent, or randomly allocated. Participants in the effort-contingent condition were rewarded based on cardiovascular measures of β-adrenergic sympathetic activity during completion of the working memory task. The authors argue that such a measure is an objective way of measuring effort, compared to commonly used effort measures that rely on estimations of future effort willingness. The researchers then tested whether the effort-contingent reward group displayed a greater preference for a more demanding, unrelated maths task even when no reward was being offered. They found a significant main effect of group, with those rewarded for their effort selecting significantly higher difficulty levels than those rewarded randomly, and no link between effort and performance. They even went on to replicate both findings in a second study completed online, where half participants were rewarded with increasing amounts of money for increasing difficulty (as a proxy for increased effort given it being online), and half rewarded randomly. With regards to the null findings between effort and performance in both studies, they point out that the high effort choice people had to complete harder tasks, which you would expect to have caused lower performance compared to those choosing easier tasks. Therefore, because Clay and colleagues found such individuals mobilized high effort to complete the harder task just as well as those completing easier tasks, they can argue that rewarding effort led to not only changes in an isolated effort choice, but also in exerted effort.

The idea that rewarding effort may increase future effort willingness is further supported by recent data of 761 responses from Lin et al. (2024), who also show that rewarding effort choices, rather than on performance, increases participant's willingness to choose harder tasks, even when unrewarded. clearly dissociates the effect of rewarding people for choosing effortful challenges and performing well and suggests that rather than rewarding performance as a proxy for effort, rewarding effort directly may be a more fruitful strategy in promoting future bouts effort. While such an idea is exciting, exactly how best to measure effort (and thus reward it), is an ongoing discussion, and the focus of Chapter Two of the current thesis.

An interesting avenue of future research relates to disentangling the relative contribution of the value of effort in terms of the outcome, and the valuation of the effort itself. This could be measured using careful experimental design. For example, one could design an interleaving within-subjects design study whereby participants make multiple effort-based judgements over the course of the experiment. This would be an extension to Vinckier and colleagues (2019), who assessed how the desirability of a food reward item changes over time based on whether that food item was associated with high performance, and high effort. They found that performance, but not effort, increased desirability. Therefore, in a similar way, one could imagine a study in which prior and posterior effort judgements could be understood in terms of the effort-based choices that the participants make. Such a study would be in line with lab studies showing that abstract shapes associated with high effort to get a reward are subsequently preferred to shapes associated with low effort for the same reward, suggesting that the effort positively impacted value (Alessandri et al., 2008, Aronson & Mills, 1959, Klein et al., 2005). The findings may also be relevant in the literature looking at the 'fruit of labour' and effort justification. While it could be that the success or failure of a task is acting as a proxy for the individual as to the effort invested, these studies show that people devalue negative outcomes of chosen actions; referred to more formally as post-failure devaluation.

Individual Differences in Effort Willingness

Given that effort is typically viewed as a mediator between an individual's capacity and goal attainment, rather than simply an external quality of the choice scenario (e.g., as in the case of other aspects such as reward delay and probability), it is relevant to briefly discuss individual differences in effort willingness. As highlighted by Westbrook et al. (2013), effort calculations are likely not only sensitive to the unique demands of the situation, but also of individual factors such as age or NFC. Specifically, they found effort discounting to significantly correlate with NFC, where lesser effort discounting predicted greater self-reported engagement with demanding activities as measured using the Need for Cognition Scale (Cacioppo et al., 1982). This supports the idea that differences in effort willingness may be caused in part by trait-like differences in the way that effort costliness is perceived. This makes sense when considering effort in daily life. On the one hand, there are many effortful activities which one could think of that are aversive (e.g., doing the dishes), and others that are effortful yet less aversive (e.g., playing video games). At the same time, an activity considered effortful to one person, such as reviewing a thesis about effort, may not be considered as so to another. In a study looking into the role of the task and the individual on effort in 2020, Ackerman et al. demonstrate that preferences for undertaking, versus avoiding, an effortful task is not simply determined by the task, but also moderated by individual preference for certain types of tasks. Specifically, they found differences in disutility appraisals of similarly effortful tasks. For example, moderately demanding tasks, such as visiting a museum, were characterised by high variability in judgements of disutility. Importantly, they found that specific trait-like features moderate such relationships. Specifically, they found personality trait measures such as Mastery and Openness to Learn constructed from the International Personality Item Pool (Goldberg, 1999) using factor analysis to significantly correlate with effort-based task preference. Therefore, the SV of effort may differ depending on the individual's capacity in relation to the task demands, as well as individual preference towards certain types of tasks over others based on trait individual differences.

While the notion of effort adding value for its own sake is an attractive one and may be relevant for interventions, it is important to consider that effort likely always carries a cost of some kind. This is because even if it were possible to set up a life in which every effort was met with reward, such that an individual could learn to value effort totally and to not perceive it to be a cost, one would still want to be strategic in your efforts such as to avoid missing out on potentially more rewarding alternative actions. Therefore, it would still be beneficial to attach an opportunity cost to effort in order to encourage the development of optimal habits. Accordingly, it is likely that effort is simultaneously costly and valued.

Effort is Costly and Valued

Taken together, these findings suggest that effort can be costly, increases the value of outcomes, and may also itself become valued. Considering effort as both costly and valued may explain why matching task demand to ability leads to positive effect (Csikszentmihalyi, 2009). By accounting for the fact that effort can also be a rewarding aspect helps to explain why a more effortful choice is chosen over an effortless or lesser effort condition even when they lead to the same nominal outcome (e.g., financial reward). Therefore, this explains why people may find solving a more complex maths problem more effortful than an easier one but find answering the more difficult problem to ultimately be more satisfying, i.e., it has greater overall value. Accounting for the costs and benefits of effort also explains why personally assembled furniture may acquire a greater SV than made-to-order furniture (Norton et al., 2012).

Conceptualising effort as both a cost and value-added does mean that previously tested models, specifically the hyperbolic, hyperboloid, and exponential discounting functions, commonly used to model effort-based decisions (Białaszek et al., 2017), may no longer be most suitable. This is because they do not account for the SV of outcomes, and assume that with increasing effort, the SV of an action is always approaching, but not becoming zero. This suggests that the outcome of effort exertion always has value. However, it has been shown that, when considering a choice with equal costs and benefits, participants will choose to not engage (Botvinick, 2007). Therefore, rather than taking an extremely effortful action over receiving nothing without effort, a person would choose to not act. In this instance, we can say that the costs exceed the potential benefits, meaning that the behaviour associated with the highest expected value is to not engage with a task. Similarly, as it has been shown that effort can be increased with reward (Hübner & Schl˙osser, 2010), it can be assumed that more effort will be required for the cost function of a highly rewarded task to reach zero. Reaching a value of zero is accounted for by alternatives such as the sigmoidal cost function or parabolic discounting (Hartmann et al., 2013; Klein-Flügge et al., 2015), which may be preferable in future research.

What is the Function of Effort?

In addition to independence and aversiveness, the final consideration to be made in this opening Chapter relates to the function of effort. Given that effort is considered to have a costly component, many theories subscribe to the notion that the function of effort is to motivate an organism to behave adaptively (Kurzban et al., 2013), such as to maximise the ratio of reward to cost. Therefore, the aversive phenomenology of effort is thought to be the output of mechanisms designed to influence optimal decision-making. In such views, effort is a precious resource to be allocated wisely. Problematically however, the exact nature of this costly resource is yet to be specified at the biological and/or functional level. As highlighted by Andre et al. (2019), theories of mental effort can be divided into two types of resource models: physiological cost models, and cost-benefit models (Embrey et al., 2023; Shenhav et al., 2017). I will go through each of these in-turn, before discussing recent integrative models that argue that the function of effort is to optimise behaviour through cost-benefit analysis, but acknowledge that physiological substrates are required for this process to function, and may influence what an individual considers to be an optimal choice. I consider what treating effort as a tool for optimisation means for physiological and cost-benefit models, before finally presenting a working definition of effort that accounts for the independence, aversiveness and function of effort.

Physiological Cost Models

Physiological cost models stipulate that the function of effort is to preserve a metabolic resource consumed during exertion. Therefore, effort is linked to a metabolic resource in the brain that depletes with use (Baumeister & Heatherton 1996). Effort as a physiological cost is a central theme in models of self-control (Baumeister & Vohs, 2016), which posit that the consumption of an 'effort resource' is what underpins and individual's ability to exert effort, and the phenomenological cost of doing so (Gailliot & Baumeister, 2007; Muraven & Baumeister, 2000). Much like a muscle depletes energy as contraction becomes force (Muraven et al., 1998), effort has been hypothetically linked to a limited resource that depletes with use, with its depletion in proportion to the amount and duration of exertion. Therefore, effort costs can be explained due to the consumption of resources that might be needed later and will have to be restored through some other costly actions. From this perspective, the aversive phenomenology of effort is reflective of depleted resources (Baumeister & Vohs, 2007; Warm et al., 2008), which motivates us to allocate our efforts judiciously. This perspective is supported by many studies showing declining performance over time from one effortful task to the next

(Baumeister et al., 1998; Muraven et al., 1998; Schmeichel, 2007), as well as a meta-analysis conducted in 2010 by Hagger et al. of almost 200 studies, showing a robust medium effect.

One key claim of the physiological cost argument is that effort consumption relies on a central, domain-general resource (Muraven & Baumeister, 2000). Therefore, there is a common physiological cost of effort that is consumed no matter what type of engagement. This does not mean that different types of tasks consume the resource uniformly, but rather that it is 'paid for' in a common physiological effort currency (Baumeister et al., 2007). Such an assumption is why evidence for physiological models typically come from sequential task paradigms, that show how effort at time 1 can reduce performance on subsequent unrelated effort tasks at time 2, such as solving a puzzle or the Stroop task (Inzlicht & Gutsell, 2007; Muraven et al., 1998). Another key claim is that it is possible for the capacity of this resource to change over time, in response to experience or practice (Muraven et al., 1999). Therefore, like a muscle, resources underlying effort may change in capacity depending on experience. This parallels a similar idea in cognitive psychology that brain training can improve performance for task-specific, as well as general cognitive, measures (Thorell et al., 2009).

Blood glucose has been proposed as this precious resource. Glucose is a carbohydrate absorbed into the body during digestion and used as energy. It is known that the brain relies heavily on glucose for energy (Laughlin, 2004), and that the metabolism of glucose from the bloodstream is what allows the brain to carry out its functions (McNay et al., 2001). Blood glucose has been linked to effort firstly because extended engagement with effortful tasks has been shown to decrease blood glucose concentration (Fairclough & Houston, 2004), and low blood glucose has been linked to poor self-control (Galliot & Baumeister, 2007). Studies using Positron emission tomography (PET) imaging also show that frontal regions in the brain increase their metabolism of glucose during continuous effort (Buchsbaum et al., 1990), that increased effort is correlated with a rise in glucose metabolism (Siegel et al., 1995), and that glucose consumption reduces as skills become more automatic (Haier et al., 1992). Secondly, a variety of studies showing a relationship between performance and blood glucose

(Gailliot & Baumeister, 2007). Finally, studies show that receiving glucose can counteract drops in effort. For example, performance decrements can be eliminated by giving participants a glucose drink (Gailliot & Baumeister, 2007). It is relevant to note that a dose of glucose has been shown to have no effect on individuals not engaged in effortful activities. Specifically, studies show that low glucose impairs performance for high effort tasks such as Stroop (Benton et al., 1994), but not lesser effort tasks such as simple reaction time (Owens & Benton, 1994). This may be because controlled processes require more glucose than automatic processes (Fairclough & Houston, 2004), making glucose an important resource during effortful activities.

However, there is additional evidence that speaks against the glucose hypothesis (Kurzban, 2010; Kurzban et al. 2013). Firstly, the finding that blood glucose decreases between after effort compared to baseline has been subject to scrutiny, as researchers have observed that this is not always the case. For example, studies have shown blood glucose consumption to increase no more than 1% during vigorous task engagement (Raichle & Mintun, 2006), and overall metabolic demands to change little in the brain during task engagement (Kurzban, 2010). Secondly, explaining effort in terms of blood glucose alone fails to explain instances of sustained attention despite diminished levels of blood glucose e.g., after intense physical activity (Kurzban, 2010; Kurzban, 2016). Overall, the available evidence suggests that blood glucose does not directly map on to ‘effort’. It remains possible that more blood glucose is made available from stores during effortful engagement, and differences may be related to individual differences in participants ability to replenish supplies on and ongoing basis. However, future research is required to assess blood glucose over extended periods of effort exertion to formally test this. on to ‘effort’. It remains possible that more blood glucose is made available from stores during effortful engagement, and differences may be related to individual differences in participants ability to replenish supplies on and ongoing basis. However, future research is required to assess blood glucose over extended periods of effort exertion to formally test this. For now, blood glucose is typically considered to be an internal signal that tracks extended engagement with demanding tasks that may factor into decisions about whether to expend effort, rather than being causally related to effort expenditure. For example, in a study by Walton et al. (2013), it was found that altering a participant's beliefs about willpower determined whether blood glucose tracked self-control. This is in line with Hockey (2011), who state that blood glucose is likely to influence the effectiveness of brain operations relating to effort, rather than being the direct cause of effort.

It has also been hypothesised that neurotransmitters play a central role in mediating effort-based decision-making (Aarts et al., 2011). Dopamine has garnered the most research interest, though other neuromodulators such as noradrenaline, acetylcholine and serotonin have been implicated in signalling effort cost (Aston-Jones & Cohen, 2005). When it comes to dopamine, striatal dopamine is thought to signal task utility to direct effort (Niv et al., 2007). This is supported by animal studies showing that phasic dopamine release encodes the net SV of reward magnitude, discounted by delay or task load (Gan et al., 2010). This is supported by a rodent study by Bardgett et al. (2009), who find that d1 or d2 antagonism lowers selection of high effort option, whereas high dopamine amphetamine administration increased high effort choice. In humans, Wardle et al., (2011) show that amphetamine enhances effort willingness, particularly during when reward was uncertain. In line with this, Treadway et al. (2021a) measured dopamine transmission using PET imaging, and found that individual differences in dopamine transmission in the left striatum and ventromedial prefrontal cortex correlated with choices to complete higher effort tasks for reward, rather than an easier less effortful version for less reward. Bilateral insula was found to negatively correlate with effort willingness. This is consistent with idea that this area encodes for response costs. Therefore, rather than directly reflecting effort, striatal dopamine signalling may shape cortico-striatal synapses to reflect the relative benefits and costs associated with effort, a notion that is discussed in more detail in the 'Integrative Accounts' section below.

Contrary to many resource-based accounts of effort that have focused on finding a limited resource responsible for effort costs, Holroyd (2016) proposed that the physiological limitation responsible for effort constraints might instead be related to the accumulation of metabolic waste during effortful tasks. Specifically, amyloid beta proteins are upregulated in their production in neural tissue during tasks that require high effort (Holroyd, 2016). Such a build-up of production versus clearance is undesirable primarily because it impedes phenomenal effort exertion (Libedinsky et al., 2013), with long term build-up also being identified as a cause of Alzheimer's disease (Helmuth, 2001). This production-to-clearance ratio hypothesis is supported in several ways. For example, it has been shown that effortful task engagement leads to increased cortical norepinephrine release (Robbins et al., 2009), driving physiological changes thought to increase amyloid beta production and decrease clearance rates (Ross, et al., 2019). Additionally, sleep has been shown to increase amyloid beta production and clearance (Xie et al., 2013), which itself is shown to increase phenomenal effort. It is important that further research is conducted to further investigate how amyloid beta proteins and effort relate.

While much work has been conducted in attempts to find a global physiological marker for effort, it is important to consider that there may be multiple dimensions of effort (Westbrook & Braver, 2015). For example, effort-related challenges presented by different force requirements (e.g., 75% versus 90% max hand grip) may not be regulated in the same way as those presented by tasks involving repeated responding, such as that seen in ratio schedules (e.g., five button presses versus ten). Additionally, as mentioned previously, it remains unclear whether a task being cognitive or physical fundamentally impacts effort-based decisions (Andre et al., 2019). In a review of the relationship between effort and depression, Horne et al. (2021) found that papers were twice as likely to report positive findings when relating depression to cognitive effort, compared to physical effort. Such findings suggest that there may be a distinction between different types of effort in underlying processes. The importance of this point is further highlighted by Hosking et al. (2015), who compared the effects of dopamine antagonists on a ratio-discounting task that assesses physical effort versus cognitive effort discounting. They found that while dopamine antagonism altered decision-making based upon physical effort, it had no effect on discounting based upon cognitive effort. Therefore, both studies suggest that a global measure of effort willingness may differ depending on the 'type' of effort the researcher is interested in. It is therefore that physiological cost models can account for effort across a range of cognitive and physical tasks.

A further drawback of physiological models are that studies show inconsistent results in relation to whether the capacity of this resource can change over time. Specifically, some show a depletion effect (Hagger et al., 2010), while other more recent replication attempts have failed (Lange & Eggert, 2014). Inzlicht and Berkman (2015) conducted a meta-analysis of 10 studies using a pre-post design and control group, and analysed both the first reported and relevant test statistic, and the last reported and relevant statistic. Using the first method, they found a small stable effect, and using the second method found an unstable medium effect.

Another concern is that even if a training effect is shown, like cognitive test training (Owen et al., 2010), it may not generalise. Additionally, a training effect in itself does not directly support the physiological model. This is because training may increase the 'amount' of effort resource available, but may be due to other factors, such as changing attitudes towards effort (Job et al., 2010), reducing its aversiveness (Botvinick, 2007; Inzlicht et al., 2015), or by increasing its automacy (Gillebaart & De Ridder, 2015). This is demonstrated in the recent effort training study by Clay et al. (2022), who investigated whether effort could be increased over time through effort-contingent reward, but did not commit to whether it is a physiological resource that is being increased, or whether the intrinsic value of effort itself increases for other reasons, such as due to participants perceiving effort as a cue for reward.

A final outstanding question relates to the timescale to which effort depletes and is replenished. Classic findings suggest over a short period of time in the order of minutes and hours. Recent studies suggest this may not be the case (Carter et al., 2015, Hagger et al., 2016). It may be that effort recovers only over longer timescales (Blain et al., 2016).

From the above, while amyloid beta proteins likely relate to effort, and dopamine is associated with effort-based choices, no clear biological resource that is consumed during effort exertion has been found (Inzlicht et al., 2014; Botvinick & Braver, 2015). Furthermore, much, if not all, of the energy consumed by the brain is used for maintaining spontaneous activity, i.e., activity that is not related to a particular effortful task (Raichle & Gusnard, 2005). It is possible that the physiological perspective may never provide an exhaustive explanation of effort, as in the case of physical efforts, it has been shown that effort can arise without the cost of motor control (Morel et al., 2017). For cognitive efforts, the idea that brief cognitive effort exertions can meaningfully deplete a resource seems implausible, given that such a resource is yet to be identified despite many efforts to do so (Kurzban, 2010). Additionally, even if a particular physiological cost were to be identified as reflecting effort exertion, this would not elucidate how or to what extent such a physiological cost is allocated for different tasks. Therefore, to echo Holroyd (2016), it is safe to conclude that a conclusive global metabolic cost of effort has yet to be presented.

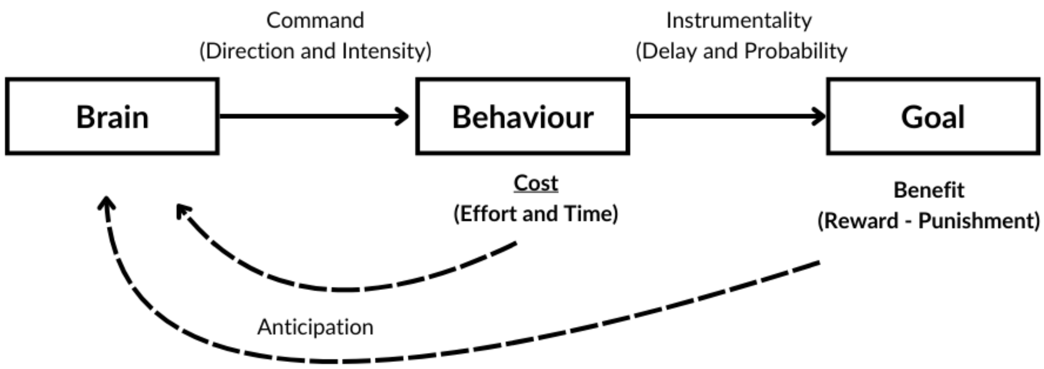
Cost-Benefit Models

A relatively new theoretical development in the effort literature is to view effort as an important variable in an individual's cost-benefit calculations when deciding their behaviour. These approaches are sometimes referred to as economic decision-making models of effort, as they model behaviour as a trade-off between the costs involved in a course of action, and the benefits of engagement (Shenhav et al., 2017). Therefore, such models stipulate that the function of effort is to guide behaviour to the option associated with the greatest reward of the available options, in relation to their cost (Kurzban et al., 2013; Shenhav et al., 2017). In the same way that hunger incentivises us the pursuit of food, effort is thought to drive behaviour towards reward (Kurzban et al., 2013; Otto & Daw, 2019). The main of objective for researchers becomes trying to quantify the costs and benefits and relate these variables to behaviour.

One prominent cost-benefit model is the EVC model (Shenhav et al., 2013), originally proposed as a normative model of value calculations conducted in the anterior cingulate cortex. As discussed earlier in this Chapter, the EVC model stipulates that behaviour is determined by a cost-benefit analysis relating to effort. The model stipulates that the value of a reward can be discounted by aspects such as likelihood of performance and in-turn likelihood that high performance will lead to high reward. This is similar to the model from Pessiglione et al. (2018), where effort is situated as a cost that is offset by reward or the avoidance of other costs such as punishment (Figure 3; Pessiglione et al., 2018).

Figure 3

Schematic View of Motivation from Pessiglione et al. (2018). Permission was Granted for Use of This Figure by Brain Through RightsLink



As the physiological mechanisms of physical exertion are well understood, cost-benefit models are well-equipped to explain the resources consumed during physical efforts. For example, we can explain a curtailment in effort as a result of available glucose resources or the ability to discharge metabolic products such as lactic acid. Therefore, while the decision-making process for physical efforts remains a complicated affair, there is at least an absolute reference of physiological constraint (Morel et al., 2017). However, cost-benefit models such as the EVC and the one by Pessiglione et al. (2018) struggle to specify the exact nature of this cost for cognitive efforts (Shenhav et al., 2017). The source of cognitive effort costs have typically been explained in two ways: relating to properties of the cognitive system (e.g., limited capacity), or environmental conditions (e.g., alternative choice options), and their interaction with the cognitive system.

When it comes to properties of the cognitive systems, researchers have focussed on metabolic constraints, as discussed earlier in this Chapter, as well as structural and representational limitations of the cognitive system. Structural constraints refer to constraints on the working memory required for highly complex cognitively demanding tasks (Hunt & Lansman 1986). Such a perspective well explains why increasing demand would lead to greater cost, but does not explain why effort would become more subjectively costly over time (Hagger et al., 2010). When it comes to representational limitations, it is argued that cognitive effort costs arise from shared use of representation between tasks (Shenhav et al. 2017). Such shared representations allow for inference and generalisation at the cost of multi-tasking capacity (Musslick et al. 2016), therefore leading to conflict during concurrent task execution. To prevent such a detriment, it is argued that cognitive control limits the number of processes relying on shared representations (Musslick & Cohen 2019). Both theories on structural and representational constraints fail to explain instances where reward can increase cognitive effort exertion (Camerer & Hogarth, 1999).

The second branch of cost-benefit calculations focus on the fact that allocation of limited resources requires choosing from various options. From this perspective, it is the depletion of computational capacity that is the 'cost' of effort (Inzlicht et al., 2014; Kurzban et al., 2013), where the feeling of effort is the output of a computational mechanism that indexes this cost. Such mechanisms are viewed as necessary due to constraints on our information processing system, whereby only a limited number of processing units can be devoted at a time to effortful control (Hockey, 1997; Shenhav et al., 2017). From this perspective, effort is a signal that encourages us to remain flexible and expand our behavioural repertoire pursue different goals, with effort costs arising to promote flexibility of cognition, and assist us in choosing an action by prioritising tasks that minimise costs (Ritz et al., 2022). Such functional accounts highlight that achieving goals involves considerable opportunity costs such as time, energy, wellbeing, and other limited resources, that could otherwise we allocated elsewhere (Gigerenzer, et al., 1999). Therefore, the cost of choosing to complete a demanding task comes from being committed and not free to complete other potentially rewarding tasks. Specifically, when we engage central cognitive modules in a given task, they are no longer available for other possible beneficial tasks (Kurzban et al., 2013; Boureau et al., 2015). Therefore, opportunity costs are thought to drive a motivational shift towards less costly and more pleasant alternative tasks. Accounting for opportunity costs incurred by resource allocation helps to explain why a bias against effort expenditure exists (Kurzban et al., 2013) and why effort often feels so subjectively costly (Inzlicht et al., 2018).

Problematically, it is common for researchers to assume, rather than validate or explicitly address, opportunity costs. For example, Fiske and Taylor (1991) frequently refer to information overload when explaining why people are cognitive misers, but fail to specify the exact nature of this information overload. Simon (1990) also argued that people are limited in their computational ability, but again did not specify exactly how. Often, the relative ease or difficulty of processing several pieces of information are implied, but the mental resource to be conserved is often vaguely referred to, such as constrained 'cognitive resources' (Shah & Oppenheimer, 2008). One of the few computational cost models of cognitive control that does account for opportunity costs is the one by Miller and Cohen (2001), which posits that cognitive control involves the maintenance of task sets in prefrontal working memory (WM) circuits from which top-down signals bias processing pathways connecting stimuli to goal-directed responses. In the model, it is proposed that as both cognitive control and WM are valuable in promoting optimal goal-directed behaviour, one way to optimise goal selection would be to make WM allocation value-based. They argue that, while it is possible that such a circuit could be reconfigured to serve sub goals, an individual's ability to serve multiple goals simultaneously is limited (Cole et al., 2013). Therefore, cognitive control should be treated as a variable in decisions to engage effortful control, with allocation towards a goal coming before allocation to other potential goals. In sum, effort may reflect the opportunity costs associated with resource allocation (Westbrook & Braver, 2015), and be a mediator of an individual's strength of commitment towards achieving goals (Maslen et al., 2019), alongside other control costs such as time and efficacy (Shenhav et al., 2013).

However, opportunity cost models are not without shortcomings. Firstly, such models situate effort as a feeling that drives a shift in behaviour. Viewing effort as a feeling is problematic, as efforts are goal-directed, productive and meet resistance, which feelings are not. Secondly, viewing effort as a signal during goal pursuit also fails to explain how the intensity or difficulty of effort can change. For example, opportunity costs do not explain fatigue effects on effort (Dora et al., 2022), nor do they explain why an individual would continue with the same task engagement, but to a lower intensity (Massin, 2017). Some researchers have suggested that while effort is in principle unlimited, the connectivity of a neural network may become weakened through repeated use, and that this decrease in capacity is what constitutes a cost associated with mental fatigue experienced. However, studies testing this specific question are rare and find no direct or mediating link between opportunity costs and fatigue (Dora et al., 2022). A final shortcoming of opportunity cost models are that they fail to explain scenarios for which both opportunity costs and effort are high, such as a choice during a life-or-death scenario, where only one choice leads to survival.

To summarise, while both physiological and cost-benefit models are based on the notion that prolonged exertion of effort leads to a progressive decrease in an individual's ability to continue to exert effort, cost-benefit models aim to present processes that reflect the functioning of the brain. However, neither explanation conclusively explains effort. Specifically, physiological models fail to present a clear metabolic cost of effort, nor do they offer mechanisms by which motivational factors can influence effort. At the same time, cost-benefit models fail to clearly state what exactly the costs and benefits are, and pure opportunity cost models fail to explain effortful behaviours that incur no apparent opportunity cost.

Physiology Influences Cost-Benefit Computations

Recent cost-benefit models of effort typically acknowledge that physiological aspects do influence motivation, which in turn influence behaviour (Inzlicht & Berkman, 2015). For example, the Self-Regulation Model (Baumeister & Vohs, 2018) posits that self-regulation consumes a limited energy resource (effort), thereby producing a state called ego depletion in which cost-benefit calculations are curtailed because of low energy. A similar model by Christie and Schrater (2015), the Optimal Control Model, posits that when deciding whether to exert effort, an individual will compare the cost of limited resources to the payoff to determine if it is 'worth it'. When an individual is motivated to complete a selected behaviour, it is hypothesised that this induces people to dip into their 'ample reserves of energy' (Baumeister, 2014). Therefore, both assumptions of limited resources as well as cost-benefit trade-offs are included as different components of the same framework. However, unlike the first model, the second stipulates that cognitive costs arise from intelligent resource allocation over time, rather than because an effort resource is depleted.

It is important to note that the model above moves away from 'effort as a resource', and towards viewing effort as a variable in a cost-benefit analysis, where an individual's behaviour is explained in terms of motivation and changing priorities (Inzlicht et al., 2014). Therefore, the fundamental reason for choosing not to engage with a task is due to the task not being sufficiently interesting, important, or otherwise worthwhile enough to continue with. Such a perspectives deviate from pure cost-benefit models, as they treat effort as a resource that is dynamically utilised and replenished. For example, going back to the example of the marathon runner, it may be particularly important for an individual to consciously limit their effort exertion in order to preserve resources for the duration of the race. Therefore, in this instance, what may appear to be aversion to effort may in fact be strategic resource allocation. In such models, the goal of effort itself is to optimally maximise the overall value of engagement, accounting for costs and metabolic constraints.

The topic of optimisation has been key to arguments made by Andre et al. (2019), who argue that the weight and nature of the costs relating to effort change depending on the situational demands. According to Andre and colleagues, the relative importance of energetic costs change depending on whether an individual is running a marathon, compared to completing another task such as an attentional task. In addition to this flexibility, they propose that the opportunity cost of performing behaviours may also vary, such as when an individual is free to select among several choices. Therefore, the cost of effort may increase because of opportunity cost, such as when trying to homework when having the television on in the background (Kurzban et al., 2013). In other scenarios, opportunity costs may be low or even zero.

Recent research looking at the relationship between dopamine and effort provide support for models integrating aspects of both physiology and cost-benefit computation. Westbrook et al. (2020) tested the possibility that dopamine, known to relate to cognitive control and working memory, plays a role in reducing sensitivity to costs and increasing sensitivity to benefits, as well as mediating opportunity costs. In their study, it was found that participants with lower dopamine synthesis capacity in the caudate nucleus as measured using dopamine PET were less willing to accept high-cost high benefit offers. Conversely, they found higher dopamine synthesis capacity in the caudate nucleus to predict greater selection of high effort high benefit over low effort low benefit. Additionally, they found that administering methylphenidate (which increases dopamine) during decision making increased willingness to expend effort compared to a placebo, but more so in those with low starting dopamine synthesis capacity. Based on eye gaze patterns, they hypothesised that dopamine increases sensitivity to benefits and decreases sensitivity to costs. They tie their findings back to the EVC and hypothesise that striatal dopamine boosts willingness to exert cognitive control by increasing sensitivity to benefits versus costs of effort.

In a separate study published a year earlier by Hofmans and colleagues (2020), it was tested whether dopamine also signalled an opportunity cost effect. This is plausible because previous research has shown that dopamine impacts behavioural rigour, but not which decision is made. They asked participants to choose between greater reward for more time on visual working memory task or less reward for unconstrained free time. Again, methylphenidate was found to increase high effort selection. However, they found that those with high rather than low starting synthesis avoided effort the most. Also, these effects mostly depended on dopamine in ventral, rather than dorsal striatal dopamine. Based on these findings, they putatively suggest that the functional impact of dopamine signalling depends on the striatal subregion, where dopamine in the ventral striatum may encode an average rate of reward to signal opportunity costs, whereas dopamine in the dorsal striatum is for effort cost benefit trade-offs of opposing actions. Regardless, both studies demonstrate that a complete understanding of decision-making and the role of effort requires an acknowledgement of the role of physiological aspects, such as dopamine synthesis.

So, What Is Effort?

As discussed, effort: A) Is an independent construct distinct from attention, fatigue, task difficulty, risk, grit, need for cognition, cognitive control, and motivation. Research indicates that effort reflects a key aspect of motivation, which is a determinant of cognitive control allocation, i.e., goal-directed behaviour. B) Influences an individual's subjective estimations of cost and benefit relating to a candidate task. Many studies find evidence for a cost-benefit trade-off in decision-making, with researchers identifying that effort is both costly and valued. C) Facilitates adaptive decision-making and is reliant on physiological substrates. Studies have shown that effort-based decisions are systematic, and yet influenced by physiological aspects such as neurotransmitter synthesis. So, with these points in mind, what is effort?

The reality is that an agreed definition of effort does not exist (Thomson & Oppenheimer, 2022). With that in mind, some define it as 'the subjective intensification of mental and/or physical activity in the service of meeting some goal' (Inzlicht et al., 2018). Such an approach justifies effort manipulations that include creating quantitative differences in the intensity of a type of an effortful task (e.g., by increasing the number of n on an n-back task). However, constricting effort to an intensity is problematic, as the space of factors that influence effort may also be qualitative, and so it is therefore difficult to say whether the sustained maintenance of information in working memory compares to other tasks that could be effortful, such as those involving sustained attentional vigilance. Therefore, it has been argued that looking at effort purely as an intensity makes it difficult to know how effortful processes are without direct measurements and makes it difficult to refine measurements without a clear intensity standard with which to calibrate (Thomson & Oppenheimer, 2022).

Others posit that effort implies the mobilising of resources (Hockey, 2011). However, as with many definitions of effort, it is unclear what these resources are. Other researchers focussing on the link between motivation and cognitive control situate effort as a motivational cost that mediates cognitive control allocation (Botvinick & Braver, 2015, Shenhav et al., 2013). Such accounts are promising, as such a position can be expanded to allow effort to be both a costly and a beneficial component. However, again, exactly what the cost of effort is not explained, nor whether effort can be a benefit.

As discussed, leading theories stipulate that effort is a variable in the cost-benefit analysis that occurs when an individual is deciding on whether/how intensely to engage with a task. However, as mentioned, a key challenge is that 'effort' seems to both increase (Ma et al. 2014, Norton et al., 2012), and decrease (Westbrook & Braver, 2015), participants SV of reward. Given that there is still a lack of consensus in the literature with regards to what exactly constitutes effort, this begs the question of whether effort is a cost or a benefit at all, or rather as a coordinating process of value judgements. Therefore, rather than being a specific cost that directly influences the expected value of a behaviour, I will now explore the possibility that effort may reflect an individual's general willingness to undergo cost. In this way, effort reflects a willingness to pay the price of potential behaviours, whether metabolic, computational or functional, by biasing perceived costs and indirectly influencing the expected value of available behaviours. I will now spend the remainder of this chapter exploring this alternative perspective.

Effort As a Facilitator of Optimal Decision-Making, not a Specific Cost or Benefit

As argued by many researchers, decision-making involves a process in which an individual's estimate the value of anticipated outcomes based on costs and benefits. This value estimation is then compared to value interpretations for different tasks, as well as for the same task at different intensities (Shenhav et al., 2013). Such a value ranges from the lowest expected value and thus costliest thing possible, to the highest expected value and most highly rewarding. There are many things that influence the value of a task, such as reward, delay, risk etc. For example, something could be highly rewarding and so subjectively high value not accounting for anything else. However, if I were to make you wait 100 years to receive the reward, then the reward would lose much of its SV and would lessen its value.

I agree with Kool and Botvinick (2018) in the sense that effort does mediate between how well an organism can potentially perform a task and how well they do. However, I do not conceptualise effort to be the intensification of mental activity, which suggests that effort is something we directly control, and monitor through cost-benefit calculations. I also do not interpret effort as being a 'cost' of cost benefit computations as would be suggested by recent work (Andre et al., 2019).

While I agree with the overall notion that a cost-benefit analysis takes place during decision-making and influences the relationship between an individual's potential for behaviour and their actual behaviour, I tentatively considering an alternative perspective as to the exact nature of effort. I consider whether rather than relating to a specific cost, as would be suggested from prominent incantations of effort theory (Frömer et al., 2021; Pessiglione et al., 2018; Shenhav et al., 2013), could effort work as a coordinating process by influencing the estimated value of a task up or down? Therefore, rather than being a component of the decision-making process that supports optimal decisions, could 'effort' be a feature of the decision-making process itself?

It must be stressed that the distinction from effort as a component in the calculation of value, to a component of the calculation itself is not a novel one. Researchers have previously defined effort as a coordinating process that adjusts the balance of input and output operations, and as a mediator of high-level feedback from response outcomes (Gopher & Sanders, 1984; Hockey, 1997). However, without frameworks such as the EVC (Shenhav et al., 2013), it remained unclear how such an effort provided the computational basis for central decision processes in a literal sense. One possibility is that effort is a function that influences our estimations of value by biasing the weighting of costs and benefits. Therefore, it is a function fulfilled by the brain in the process of cost-benefit computation. An individual with high effort willingness therefore refers to someone who discounts the costliness of costs, such that they do not influence the expected value of an outcome to the same extent as an individual with low effort willingness. As a result, the benefits or payoff from task engagement for example at a higher intensity are subjectively more 'worth it' for that individual. Equally, a person with high effort willingness would not require much reward to undertake a costly action. Therefore, the negative impact that cost has on the expected value of a task, regardless of whether those costs are time, glucose, attention, opportunity, or any number of costs identified in the literature, will be lessened for an individual with higher effort willingness. To formalise this perspective, I consider whether effort may reflect: 'An independent cost function that mediates the SV of a candidate task by biasing perceived costs'.

$$Expected\,Value\ =\ Benefit/(Cost * Effort\,Willingness)\ (1)$$

The above perspective is qualitatively different from Andre et al. (2019), as it refers to effort in the way that cost is evaluated, rather than effort being a cost itself. Therefore, rather than the nature of the effort cost changing, could it be that 'effort' refers to the way in which specific costs are subjectively evaluated. This means that while an individual may have a preference for a task that is associated with a greater expected value and less cost (e.g., opportunity costs, metabolic costs), this does not mean that their effort willingness is necessarily higher for such a task. Instead, the individual may have a trait-like assessment of cost that they apply to all tasks they encounter, and the preference for one task over another is due to specific costs relating to the candidate tasks, not due to differences in effort willingness. Such a definition of effort works well in explaining athletes, who are seemingly willing to forgo cost to reach a goal despite high costs associated with doing so. From this perspective, they discount the value of a task to a lesser extent, compared to someone with lower effort willingness.

Effort as a mediator of value can be used to explain why studies have shown both consistency and differences in seemingly effort-based decisions. For example, the presence of a domain-general effort function would lead to correlations between decision-making across both cognitive and physical tasks, such as those found by Ostaszewski et al. (2013). It also explains why Culbreth et al. (2019) found daily physical exertion of effort to relate to decisions relating to a cognitively demanding task. A domain general effort function also explains why global physical fitness positively would relate to academic achievement, as in Castelli et al. (2007).

A domain general effort function is also not necessarily contradicted by studies showing domain specificity. For example, while Lopez-Gamundi and Wardle (2018) found only a moderate relationship between willingness to exert physical and cognitive effort, it is possible that differences in participants choice behaviour were attributed to the increased difficulty of the physical effort task, particularly during later trials. In a neuroimaging study by Schmidt et al. (2012) showing separate task-dedicated regions for cognitive versus physical effort tasks, common neural bases were also found in the cortico-ventral basal ganglia circuit, including particularly the ventral striatum. It is thought that the VS gathers cost information from the dACC, given the many studies implicating this area during effort-based decisions (Aston-Jones & Cohen, 2005; Shenhav et al., 2013; Walton et al., 2003). Finally, a study by Hosking, et al. (2015), showed that rodent's willingness to exert physical and cognitive effort were moderately related. At the same time, they also found that when treated with a dopamine antagonist, only willingness to expend physical effort reduced. Both findings are aligned with a domain general effort that influences perceptions of cost. This is because the correlations may be driven by this underlying effort willingness that is used for both the physical and cognitive tasks, and the second finding can merely show that the variables that are important for physical effort include more heavily onto dopamine. This does not however mean that the fundamental difference in the way estimations of future value were made.

To zoom out slightly, I am considering effort as a function fulfilled as part of the wider process of motivation. It is perfectly possible that someone could have high effort willingness, i.e., they discount costs of engagement and value rewards more highly, but low motivation due to a lack of available options. Conversely, an individual can have low effort willingness but be highly motivated due to an abundance of highly subjectively valuable available task options. I propose that what is commonly interpreted as effort is in fact the outcome of a value computation resulting in the allocation of cognitive control. For example, when running a marathon, rather than consuming an effort resource, a runner in fact consumes whatever is required for the race (e.g., glucose). Therefore, effort research is no longer directly tied to the task or trying to identify the costs and benefits of task engagement. Instead, effort concerns the way in which value calculations occur, which itself drives behaviour. Therefore, someone with a high effort willingness will discount costly aspects more greatly, and/or discount rewarding aspects to a lesser extent. In contrast, the SV of an option for them would decrease quicker in line with rising costs and increase more slowly with increasing rewards. Due to changes in the SV of running a marathon, person A may continue to finish the marathon despite rising costs, whereas person B will stop running. In this way, effort willingness influences the choices we make. This perspective also nicely fits in explaining why an athlete is willing to repeatedly engage in a costly action such as going to the gym every day. It is because they discount the cost and do not discount the benefit of task engagement. Therefore, even a small 0.1% gain in the sporting ability will be deemed ‘worth it’. Such individuals may also be considered ‘gritty’, if they sustain such high effort willingness over time (Duckworth, 2016).

The above definition circumvents the issue of having to define a global cost or benefit of effort, because now the exact specifications and relevant aspects of a behaviour can change depending on the task in question, with underlying effort willingness staying relatively stable. Considering recent effort training studies (Chong et al., 2018; Clay et al., 2022, Lin et al., 2024), it is possible that the trait-like effort described here may be subject to ongoing adjustments over time based on experience. For example, the extent to which the subjective costs and benefits of task engagement are adjusted can be updated based on feedback from behaviour e.g., whether a payoff was achieved. However, this requires further exploration. It also remains to be tested whether studies showing an increase in ‘effort’ in response to increased dopamine synthesis, reflect changes to effort, i.e., a mediator of cost, or whether it influences the costs and benefits themselves, which is in turn adjusted by effort.

How Effort is Defined in the Current Thesis

Effort has been understood by previous researchers in several ways, such as the intensification of mental activity (Inzlicht et al., 2018), the mobilisation of resources (Hockey, 2011), and as a motivational cost (Botvinick & Braver, 2015, Shenhav et al., 2013). However, as previously discussed, such definitions are difficult to directly observe or measure (Thomson & Oppenheimer, 2022). For example, defining effort as an intensification of mental activity does not explain what is constitutes a meaningful in activity, and does not explain different types of effort exertion in different contexts. Equally, defining effort as the mobilisation of resources does not explain the underlying mechanisms that determine when and why effort is exerted. Such a perspective also assumes that all resource mobilisations are effortful, which speaks against the literature on automatic processing (Jolley & Pashler, 2020). Finally, the definitions situating effort as a motivational cost requires effort to be a cost and do not account for people who seem to gain value from the apparent cost of effort, or when such tasks are perceived as enjoyable or rewarding (Cacioppo & Petty, 1982).

Here, effort is defined as a constituent of decision-making, that influences the way in which individuals evaluate the SV of candidate tasks before them. Specifically, I have defined effort as a willingness to endure costs associated with task engagement. Therefore, rather than being a component within the decision-making process, I propose effort to reflect how individual’s evaluate cost. Rather than being the costly component that directly reduces the SV of potential reward, I propose that effort indirectly influences SV by biasing the subjective costliness associated with task engagement. From this perspective, an individual with greater effort willingness will not discount the value of a task to the same extent as someone with lower effort willingness, in response to what may be objectively the same cost. Abstracting effort willingness from SV circumvents the issue of defining the effort cost for every possible task, and instead puts the focus on understanding commonalities in how decisions are made across different contexts. This approach matches the grit literature, whereby grit is defined as passion and perseverance for long term goals I.e., the sustainment of effort over time (Duckworth, 2012). Therefore, rather than tying grit to a particular task, it instead refers to a trait-like characteristic that can be influenced by situational and personal experiences. While grit can differ in certain areas of life compared to others, it remains a useful predictor of many outcomes such as academic achievement (Duckworth et al., 2007), career success (Duckworth & Quinn, 2009) and health and fitness (Hodge & Blanchard, 2016). Like grit, effort willingness may also change over time and in different contexts, though still predicts real-world behaviour and has clinical relevance, as would be suggested by recent research using decision-making paradigms (Crawford et al., 2023; Gold et al., 2015).

In the following chapter, the largely separate literature on how effort is measured is covered. Importantly, I end Chapter Two by tying together the effort definition given above, i.e., as a willingness to endure cost, to how effort is measured. Therefore, how can an individual's willingness to endure cost be quantified in a scientifically useful way?

Summary

To summarise, current leading theories stipulate that decision-making is a motivational process that determines cognitive control, the allocation of which is based on a cost-benefit analysis. Contrary to previous models, rather than interpreting effort as a specific cost or benefit, I have ended this Chapter by tentatively exploring whether effort could reflect a cost function that influences value estimations, by biasing perceptions of cost. Defining effort in such a way means that it is no longer a cost or a benefit. Instead, the costs and benefits become entirely specific to the task in question, with effort influencing subjective costs estimations. Such an interpretation means that an individual with high effort willingness (i.e., someone who more greatly discounts the 'cost' associated with a task) can still be unmotivated to perform certain tasks, simply due to a lack of reward. On the other hand, this perspective can explain why someone with low effort willingness (i.e., someone who subjectively estimates costs to be high) can still be motivated to perform a task, provided the costs are sufficiently low.

In Chapters Three and Four, I conduct experiments with the aim of understanding the nature of effort in more detail. Firstly, I look to understand the domain specificity of effort, and whether effort willingness fundamentally differs between cognitive and physical tasks. Therefore, I am not testing whether people assign a higher EVC to cognitive versus physical tasks per se, but rather whether there are systematic differences in the way that effort-based decisions occur between cognitive and physical tasks. Such research is valuable, as it informs leading decision-making theory and has the potential to increase the generalisability of largely separate lines of cognitive and physical effort research. Secondly, I look to understand to understand the role of affect and competence within a domain. Such research has the potential to expand current theory and improve our understanding of the role of these aspects on expected value estimations. Understanding the role of competence may be particularly relevant to research suggesting that effort can be trained and assist our understanding of genetic versus environmental influences on effort willingness.

CHAPTER TWO: HOW DO YOU MEASURE EFFORT?

Introduction

Given the many ways in which effort has been defined in Chapter One, it is unsurprising that there does not exist a universally accepted measure for effort. However, it is relevant to note that even if a definition of effort were to be accepted, this does not ensure that a single measure would emerge as a result. On this point, Thomson and Oppenheimer (2022) use the analogy of money and point out that while it is a well understood limited resource, research teams may still measure it differently depending on their particular interests, such as how it is budgeted, spent, or how much things cost. The same is true for effort, where researchers may devise different methods for many reasons, such as whether they are interested in understanding cognitive or physical behaviours, over shorter or longer periods of time, for certain types of rewards, to name a few examples. However, by using various measuring tools across studies, confusion can ensue. It is also important to acknowledge that participants themselves will differ in the way that they define effort. As will be presented later in this thesis, we find that when asking 386 participants what effort meant to them from a pre-specified list, we found no single definition to stand out. We find participants define effort as engagement, paying attention, being motivated, struggling, thinking a lot, getting tired, expending a resource, or exerting a force. It is therefore relevant to discuss effort not only from a theoretical perspective, but also from a methodological one. This chapter does just that and complements the first chapter by critically examining key measures of effort.

Measuring effort not only allows us to formally test our theoretical models, but it also has many potential direct applications. For example, measuring effort effectively may be helpful clinically in detecting disorders and adjust interventions, where patients perform in the normal range for cognitive tests (Gregory et al., 2017), while experience changes in effort-related processes. This is because changes in effort may precede cognitive decline (Aurtenetxe et al., 2013). Therefore, measuring effort effectively could help to increase the sensitivity of cognitive testing. Measuring effort effectively could also be useful in areas such as education, the workplace and sport, where such a metric could give insight in predicting success. However, creating measures of effort forces us to consider some fundamental questions about effort, such as what aspects that should be systematically manipulated in order to meaningfully test ideas. How do we know that we are measuring effort and not other aspects such as ability? Does it matter if the task we use is of a cognitive or a physical nature? Does it matter if the task is more or less enjoyable? Therefore, in addressing how best to measure effort, we touch upon the key issues which are addressed in chapters three and four of this thesis, which are the domain specificity of effort and the role of competence and affect.

To get an overview of the range of measures that exist, I will follow Thomson and Oppenheimer (2022) in grouping them into task performance, process tracing, physiological, and metacognitive measures. Of these, I will pay particular attention to choice-behaviour tasks, which belong in the metacognitive branch and measure effort in terms of a subjective willingness to engage in different behaviours. These tasks involve observing participants' behaviours; typically people's tendencies to choose one task over another, and rely on the assumption that people behave in accordance with estimated values of behaviour, in line with the EVC theory (Shenhav et al., 2013). Therefore, the goal of these measurements is to quantify the influence that effort has on these value computations. I argue that choice-behaviour tasks are preferable, as they can be easily adapted to compare effort-based decision-making across tasks of a cognitive and physical nature (Lopez-Gamundi & Wardle, 2018) and facilitate investigation into how decisions about effort are made (Westbrook & Braver, 2015). For example, with choice-behaviour tasks, it is possible to manipulate aspects such as reward and task difficulty incrementally to assess changes in the expected value assigned to different scenarios. This can be done in a way that is simply not possible with typical self-report. Being able to do so also provides a basis for more accurate taxonomic classifications and understanding of disorders of motivation (Culbreth et al., 2018; Culbreth, et al., 2016) than self-report. This is because they can be used to ascertain more specific scenarios in which clinical and control populations differ, that again are not possible with self-report alone.

In particular, I critically consider the Cognitive Effort Discounting Task (COG-ED; Westbrook et al., 2013), the Effort Expenditure for Rewards Task (EEfRT; Treadway, et al., 2009), the Effort Foraging Task (Bustamante et al., 2023), the Accept/Reject Apple Task (Chong et al., 2015), and the Cognitive Effort Motivation Task (CEMT; Ang et al., 2022). I also consider outstanding methodological questions and provide a summary table of the above measures. In doing so, I hope to demonstrate the sheer range of ways that effort has been measured, and the need for greater clarity around certain key aspects of measurement design, namely whether a task being cognitive versus physical matters, and whether aspects such as competence and fun should be controlled for and how.

Performance

Many researchers manipulated difficulty levels of cognition tasks, such as the n-back and Stroop tasks as measures of effort (Westbrook et al., 2013; Inzlicht & Gutsell, 2007). Such measures are based upon the notion that effort results from exerting resources in the pursuit of a goal or in response to declining performance (Ackerman & Thompson, 2017; Kahneman, 1973). From such viewpoints, effort is viewed as a resource that is available to be deployed in response to demanding situations (Kurzban et al., 2013; Inzlicht et al., 2014; Shenhav et al., 2017). Typically, performance is measured in terms of response quality (e.g., accuracy and error rates, response times) during control-demanding situations (Akçay & Hazeltine, 2007; Dreisbach & Fischer, 2011; Smith & Walker, 1993). Such a conceptualisation of effort is supported by many studies showing the gradual reduction in performance and efficiency over time because of prolonged effort exertion (Brisswalter et al., 1995).

As well as for cognitive tasks, effort has also been measured by asking participants to perform physical tasks involving hand gripping (Hartmann et al., 2013, Mitchel et al., 2004), climbing stairs (Ostaszewski, et al., 2013), and button pressing (Gold et al., 2015; Treadway et al., 2009). When it comes to hand grip, high effort is a greater proportion of the participants maximum grip strength. For climbing stairs, it is a greater number of flights to climb for reward. For button pressing, it is typically a greater number of button-presses in a set period. In all cases, it is assumed that increased effort is the ‘cost’ required to achieve performance.

However, there are limits to the inferences that can be drawn from using performance as a measure of effort. This is because two people can obtain the same performance through exerting different levels of effort, where one may need to work laboriously, and the other is able to perform with minimum effort (Paas et al., 2003). Therefore, prior knowledge and skills relating to the task in question can confound performance as a reflection of effort (Borghini et al., 2017). As demonstrated by Musslick et al. (2019) using computational modelling, performance only reliably estimates the cost of effort when estimates such as task automacy, reward sensitivity, and accuracy bias (the value an agent assigns to being correct) are explicitly defined. Such findings suggest that there is not a one-to-one mapping between effort and performance and are in line with many studies showing that while effort can be correlated to reduced accuracy and responses over time (Faber et al., 2012), so too can sustained attention (Petrilli et al., 2006), lack of sleep (Dawson & McCulloch, 2005), boredom (Whelan et al., 2020). In addition, studies have also shown that nonmonotonic relationships between effort and performance are also possible (Baumeister, 1984; Yerkes & Dodson, 1908). For example, as discussed in Chapter One, effort may also have influence on performance to a point, such as during data-limited tasks, but then no longer influence performance (Norman & Bobrow, 1975). For example, detecting a sound within a background of noise may be influenced by effort to a point, but then is solely dependant on the quality of the data from then onward.

In sum, performance metrics may only provide a crude estimate of effort since they are likely to decline only when task demands exceed capacity. Consequently, performance is decreasingly used as a direct measure of effort. Instead, effort is typically conceptualised as a mediator between an individual's potential/capacity for performance, and their actual performance (Shenhav et al., 2013). Therefore, the goal of effort measures has become in essence to understand the dynamic relationship between effort and performance, where at times they can be tightly coupled, e.g., during high performance efficacy, and at other times be less so.

Process Tracing

Rather than looking at performance, some researchers have chosen to focus on underlying cognitive processes that are related to effort. When it comes to mental-processes, researchers typically attempt to quantify the number of mental ‘steps’ that a person goes through during a given task. The elementary-information-processes approach (Johnson & Payne, 1985) is considered the ’gold standard’ of such models and seeks to find a common unit to measure all different types of thought.

A typical process tracing study presents participants with different options each associated with differing attributes. The key dependant variables from this are what participants look at, in what order, and for how long while they evaluate candidate options, and physical interaction with information, measured using computer cursor movements, verbal protocols, eye movements, and verbal ‘think aloud’ protocols (Jacoby et al., 1987; Payne et al., 1978). MouseTrace, developed by Jasper and colleagues (Jasper & Levin, 2001; Jasper & Shapiro, 2002), is a popular process tracing technology which has been used to infer effort by monitoring information acquisition and search behaviour from mouse recordings (Freeman & Ambady, 2010). During MouseTrace, participants are presented options that vary in reward amount and probability of reward. Beginning with nine options, participants narrow them down to three options (and one option thereafter) by either including or excluding options. The values for all options are initially occluded but revealed when clicked on, with only one visible at any one time. In this way, one can quantify many aspects such as which boxes are opened and closed, the length of time that they are opened, the order in which they are opened, and the length of time between the closing of one box and the opening of another. These data points are used to derive process measures of depth, which is the amount of information access from the available environment often associated with effort. This is exemplified in a study where MouseLab was used (Jasper et al., 2017), where individuals higher in numeracy were more likely to select highest expected value options, I.e., options with the highest reward given their probability, while at the same time taking longer with each option on display, probing the information to a greater extent, acquiring more information, and taking longer to decide. The authors argue this to represent greater 'effort' being expended when making their choice in those with higher numeracy. Therefore, the authors argue that process-tracing reflects measures of effort that leads to more optimal choices.

While the process tracing measures allow us to understand decisions for which effort seems to be related, they suffer from nontrivial challenges as a direct measure. Firstly, any attempt to separate information into 'pieces' or cognitive processing into discrete 'steps' is arbitrary by nature (Miller, 1956). For example, the number of pieces of information we perceive a participant to consider depends on the level of specificity to which we reduce the information (Kahneman & Frederick, 2002). For example, in the same way that the 'value' of a purchase can be broken down into price and quality, where quality can further be broken down into durability and craftsmanship (among other things), which again can be broken down into further constituent parts, attempting to divide effort into discrete steps oversimplifies the complexity of mental operations. Importantly, it does not account for the fact that cognitive processes involve parallel and interconnected operations that are not isolated and can simultaneously integrate information from different brain areas, such as information relating to the specific costs and benefits in question, that can be influenced by experience, time, and ability.

Physiological Measures

To overcome the issues relating to performance and process tracing measures in a way that is non-invasive to the cognitive processes being studied (Scheiter, et al., 2020), some researchers have sought to identify and characterise effort using physiological measures. As discussed in Chapter One, researchers are yet to define a single physiological 'cost' of effort in the brain or otherwise. However, some researchers have attempted to develop measures of effort based on physiological markers by studying heart rate and body motion (Haskell et al., 1993), respiratory rate (Charles & Nixon 2019), and contraction of facial muscles (Elkins-brown et al., 2016). Alternatively, those interested in cognitive efforts typically measure pupil dilation, blink rate, and skin conductance (Bijleveld et al., 2009; Botvinick & Rosen, 2009; Charles & Nixon 2019; Diede & Bugg, 2017; Kahneman & Beatty, 1966), or neural activation (Schmidt et al., 2012). Using such measures may provide a measure that is sensitive to changes in effort and allows for hypothesis testing and validation (Ayres et al., 2021).

When it comes to the heart, electro cardiac activity (Charles & Nixon, 2019), and/or cardiovascular reactivity (Gendolla et al., 2012) is typically used to measure effort. This is because during sympathetic nervous engagement, the impact on the heart has been shown to be proportional to task engagement. Specifically, beta-adrenergic sympathetic activity increases during control demanding situations, as well as in proportion to subjective task demand (Obrist et al., 1978). To measure beta-adrenergic sympathetic activity, researchers typically use the cardiac pre-ejection period (PEP), as it is a non-invasive parameter that is almost uniquely determined by beta-adrenergic activity. Systolic blood pressure, the maximum blood pressure between two heartbeats, is also commonly used. Beta-adrenergic sympathetic activity, and systolic blood pressure are preferable to other measures such as heart rate and diastolic blood pressure, which are influenced by both sympathetic and parasympathetic activity (Parati & Esler, 2012). Conceptually, those who measure effort from the heart typically root their theory to the MIT (Brehm & Self, 1989), where effort is defined as the vigour or energisation aspect of behaviour (Elliot & Fryer, 2008). Using PEP as a measure of effort, researchers finds that cardiovascular activity is closely linked to task difficulty increases (Richter et al., 2008), as well as other aspects such as ability (Wright, 1998). However, while the heart no doubt plays a functional role in how effort influences behaviour, other researchers have conducted similar work implicating the brain as a measure of effort.

According to Shenhav et al. (2013), the brain has systems specialised in evaluating costs and benefits, aggregating those to estimate a net value, and translating that into cognitive control allocation (i.e., behaviour). Functional MRI and electroencephalogram have been used to find such correlates. Brain areas implicated to reflect aspects of effort are the anterior insula (Power & Petersen, 2013), ventral striatum (Hofmans et al., 2020; Schmidt et al., 2012), prefrontal cortex (vmPFC, McGuire & Botvinick, 2010; Shenhav et al., 2017, 2019), and the anterior cingulate cortex (Aston-Jones & Cohen, 2005; Chong et al., 2017; Klein-Flügge et al., 2016; Shenhav et al., 2013; Walton et al., 2003). It is currently speculated that the SV of effort is encoded in the vmPFC (Lopez-Gamundi et al., 2021), and that the dorsal anterior cingulate cortex takes this information relating to an individual's current state (i.e., task demands, processing capacity and motivational state) as well as the estimated value of outcomes from other potential opportunities (opportunity costs) and works to determine the highest expected value of control, perhaps particularly when offers are close in SV (Westbrook et al., 2019). This net score is then thought to ultimately determine cognitive control, and be sent to premotor and motor regions, which elaborates a motor command for the muscles. It has also been shown that neuromodulators such as dopamine seem to influence the weights of cost and benefits in the net value estimation (Pessiglione et al., 2018).

However, using brain imaging to measure effort faces both methodological and theoretical challenges. Methodologically, brain imaging is typically labour and cost intensive (Prince, et al., 2008), meaning that scalability is limited. Additionally, researchers must take caution not to assume that their measure is a direct reflection of their construct of interest. This is because a brain area can be involved in multiple functions, and these functions can be draw upon many areas of the brain (Miller et al., 2013). Another challenge with physiological measures of effort generally is that factors such as stress, emotional response, engagement or general arousal may be misattributed as effort (Charles & Nixon, 2019). Finally, while brain imaging research undoubtedly facilitates the investigation into 'how' decisions about effort are made from an objective standpoint (e.g., they allow us to understand how estimations of value are conducted), they are limited in their ability to test the intricacies of 'why' decisions are made (e.g., why one task is given a higher SV than another; Westbrook & Braver, 2015). An alternative branch of effort measures, outlined below, instead focusses on understanding 'why' effort is allocated.

Metacognition

Metacognitive measures attempt to capture individual differences in which an individual decides to the extent of their effort in a particular behaviour, by asking participants to think about effort. As argued by Westbrook and Braver (2015), while subjective measures may covary with objective dimensions of task demand or reward, effort cannot be described fully in these latter terms. Two key branches of metacognitive measures, namely self-report and choice behaviour are discussed in the following section.

Self-Report

Self-report scales of effort are those that measure effort directly from individual's own reports of themselves. Measuring effort in this way is preferable to asking participants about their time spent on various activities, as simply partaking in one activity can be perceived as subjectively more or less effortful to different people (Yeo & Neal, 2008). Another advantage of self-report measures is that they can easily be developed to measure specific aspects of effort of particular interest and are more readily scalable. For example, the Need for Cognition Scale (Cacioppo & Petty, 1982), measures cognitive effort based upon participant responses to pre-determined statements focussed on their engagement and enjoyment of cognition. Similarly, physical effort can be measured based on participant reports with regards to the physical effort they had exerted in the past five weeks in terms of maintaining willpower, planning, energy, trying and discipline (Chatzisarantis et al., 2007). Another self-report measure, the NASA Task Load Index (Hart & Staveland, 1988), quantifies both mental and physical effort, based on how hard an individual rates themselves as working to achieve performance during certain tasks.

Despite the advantages of self-report, there are a drawbacks to consider. Firstly, self-report measures are only useful in specific contexts and are not sufficiently sensitive to capture effort across several scenarios (Chan, 2009). This is because self-report is restrictive to tasks that the participants have either just experienced or experienced at some point in the past. Another drawback is that self-report scales can often be unreliable. In line with this in a review of cognitive effort measures in 1994, Cooper-Martin found only three of seven self-report measures of effort to be reliable within-groups. Such a lack of reliability was hypothesised to be in-part driven by the fact that participants respond according to their unique perspective of what effort is, which can vary greatly (e.g., as a resource, engagement, force). This second drawback can be avoided to an extent by also asking participants how they perceive effort itself. Therefore, in addition to asking people questions to ascertain their effort levels, you can ask them to choose from a variety of options which best reflects how they define effort. When used alongside other measures of effort, self-report or otherwise, this can give valuable insight into how participants are responding and may explain previously found differences in responding within-subjects. Such a utilisation is also in line with the consensus that self-report measures of effort are most useful when used in conjunction with other effort measures (Greene, 2015).

Choice Behaviour

As discussed in Chapter One, contemporary theories of motivation posit that behaviour is driven by the perceived payoff of the motivational stimulus vs the costs involved in obtaining it (Salamone & Correa, 2012; Westbrook & Braver, 2015). Motivation has therefore been conceptualized in economic terms as a cost–benefit trade-off, in which the individual seeks to simultaneously maximize the expected outcome of behaviour while minimising the associated cost. Several studies have examined the effect of varying the delay (temporal discounting) or certainty of an outcome (probability/risk discounting; Cardinal, 2006) on this process. Lately, particular interest has focused on the amount of effort that subjects are willing to invest for a given reward.

Two key notions underpin measures based on choice behaviour, which are that preferences with regards to effort expenditure are systematic (i.e., that people make consistent decisions regarding the level of effort they are willing to expend in various situations), and that effort is costly. When it comes to effort choices being systematic, Dixon and Christoff (2012) showed that when asked to choose between highly effortful controlled responding and relatively effortless responding, that choice is modulated by monetary reward differences between the offers. Therefore, money can be used to consistently impact effort choice. Effort based choices are also systematic when it comes to general effort avoidance. For example, Kool et al. (2010), using the DST as an implicit measure of effort, found that most participants developed a bias against task switching and avoided cognitive-control operation. When it comes to effort being costly, as discussed previously in Chapter One, effort is commonly viewed as a cost that reduces the SV of a reward associated with it (Payne et al., 1988). This is based on Hull's Law of Less Work (Hull, 1943), and assumes that effort is a cost to be avoided or overcome by a reward of some kind. Therefore, the motivational system is designed in such a way to avoid wasting resources (Gibson, 1900).

Choice behaviour measures of effort quantify the cost of effort by measuring participant's willingness to engage in a demanding task given changes to task intensity (e.g., through changes to task requirements), and/or task identity (e.g., by changing the nature of the task in question), and reward. Quantifying effort in such a way emphasises the volitional nature of effort (Westbrook & Braver, 2015) and means that the relationships between aspects of decision-making, such as task demand characteristics, ability, and reward can be modelled. This has proven to be particularly useful in understanding the mechanisms involved in behavioural disorders such as depression, psychosis, and schizophrenia (Cathomas et al.,2021; Culbreth et al., 2018; Culbreth, et al., 2016; Horne et al., 2021).

One of the first choice behaviour measures to be developed followed the operant paradigm, whereby the participant decides how much effort to invest for a given reward. Such paradigms are a commonly used approach to determining the willingness of an animal to work for reward (Salamone et al., 1991; Schweimer & Hauber, 2005). Typically, the animal is firstly trained to perform an action for reward (Hodos, 1961). Then, in a fixed ratio version, a predefined number of operant responses are required to receive one unit of reinforcer (e.g., five lever-presses for one unit of reward; Salamone et al., 1991). In a progressive ratio version of the paradigm, the number of responses required to obtain one unit of reward gradually increases over time (Beeler et al., 2012). Relative to fixed ratio paradigms, progressive ratio paradigms have been found to generate greater response variability, which has been useful to study individual differences (Hershenberg et al., 2016). By requiring the animal to repeatedly make choices between effort and reward under conditions in which the ratio requirement gradually increases, progressive ratio paradigms can use the breakpoint as the key metric. As the breakpoint is the last ratio that the animal is willing to complete for the reward on offer, it therefore represents the maximum amount of effort that it is willing to execute for reward (Richardson & Roberts, 1996).

Studies in human participants show, in accept/reject paradigms where participants are offered a single combination of effort and reward and asked to accept or reject the given offer, that breakpoints can be increased following administration of psychostimulants known to increase dopamine (Chelonis et al., 2011). Conversely, depletion of certain amino acids known to reduce dopamine levels has been shown to lower breakpoints (Venugopalan et al., 2011). In addition, gender, and age have been shown to influence breakpoints, as demonstrated in studies on children (Chelonis et al., 2011).

A limitation of progressive ratio paradigms is that they do not assess whether the breakpoint is determined by the amount of effort that participants are willing to invest for a particular reward, or the amount of effort they are physically capable of performing for that reward. This issue may be particularly important during studies where dopamine is manipulated, as dopamine is known to influence the vigour with which physical responses are made (Niv et al., 2007), as well as enhance motivation.

An alternative to operant paradigms is to offer participants choices between multiple alternatives, for example, a less effortful task for less reward, or a more effortful task for more reward (Kool et al. 2010). Many dual-alternative tasks typically quantify effort by measuring choices between two competing options, whereby only one is permitted to be chosen (Chong et al., 2016). The classic design in rodents involves the animal having to make a choice between the two offers in a T-maze procedure (Walton et al., 2002). It is first trained to learn the locations of the less and more highly valued reinforcer, which are placed in opposite arms of the T-maze. Then, after an experimental intervention (a lesion or pharmacological manipulation), a physical barrier is added to the high-reward arm, which the animal must now overcome to obtain the more lucrative offer (Salamone et al., 2007). The rate at which the high effort/high reward offer is chosen can be taken as a proxy of the animal's motivation, and one can then compare differences in these rates as a function of the experimental manipulation.

An advantage of this paradigm over the progressive ratio paradigm is that here it is possible to separate choice (the progression of a rodent down one arm of the T-maze) from motor execution (climbing the barrier). This is because the rodent makes a choice and completes a task to gain reward, meaning that the measure of effort is no longer directly tied to performing one action or not. However, it is unclear the extent to which the animal's choices are influenced by the probability that they will succeed in overcoming that barrier to reach the reward. To overcome this reservation, the paradigm subsequently evolved to vary the amount of reward on offer in what has been termed an effort-discounting paradigm (Bardgett et al., 2009; Floresco et al., 2008). In this version, after a high-reward option is chosen, the total reward available on that arm is reduced on the subsequent trial. By repeating this procedure until the rodent chooses the small-reward arm, it is possible to derive the indifference points between two choices to calculate sensitivities to different costs and reward amounts (Richards et al., 1997).

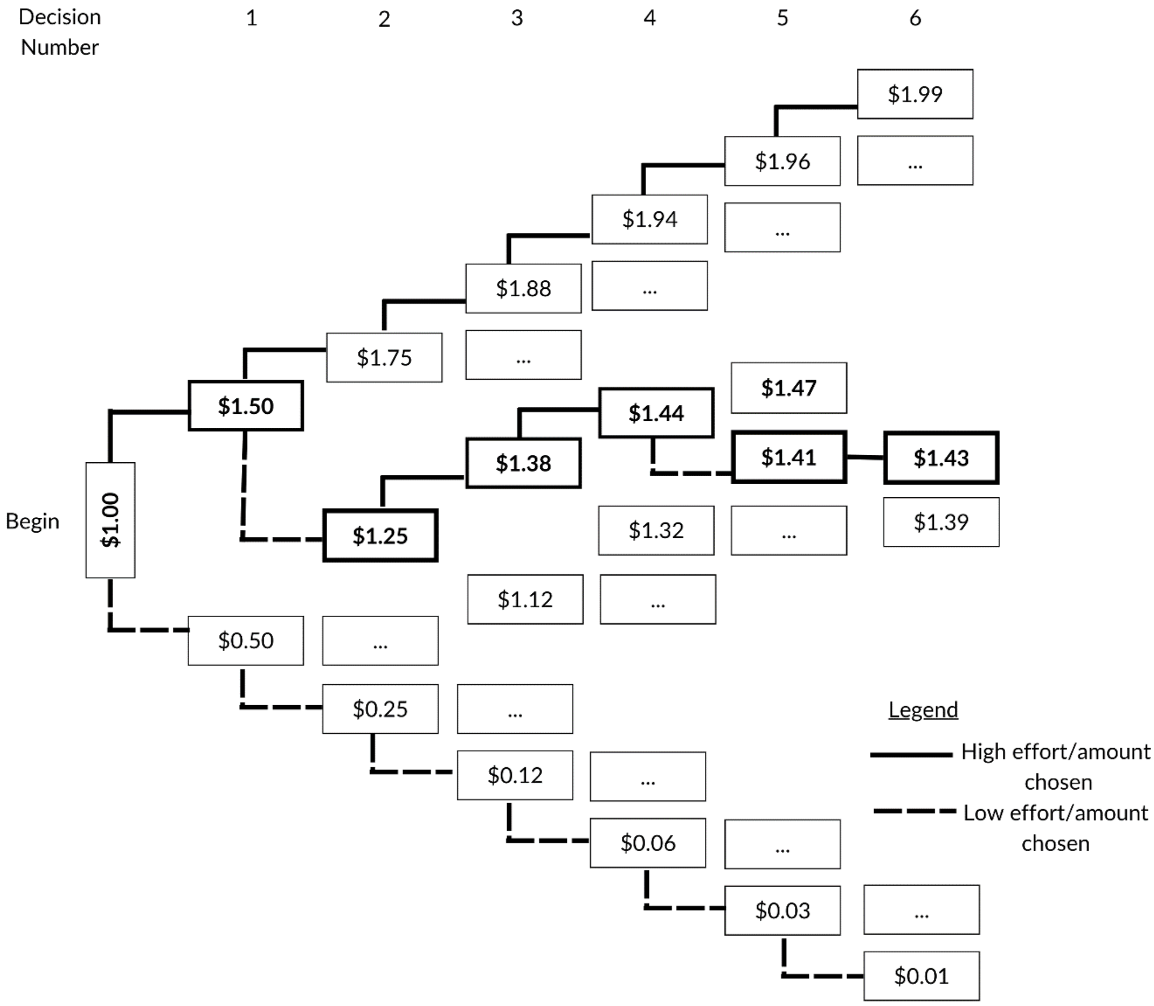
By using adapted T-maze solutions as a measure of effort, studies have shown that lesions to the medial prefrontal cortex lead to fewer effortful choices in contrast to lesions of other brain regions (Rudebeck et al., 2006; Walton et al., 2003). In addition, effortful behaviour driven by food reward can be decreased through current inactivation of the anterior cingulate cortex (Floresco & Ghods-Sharifi, 2007). In sum, by utilising the T-maze procedure, researchers have been able develop knowledge of neural regions responsible for effort-based decision-making (Hauber & Sommer, 2009; Salamone et al., 2007).

Given the utility of dual-alternative paradigms in animals, equivalent paradigms have been developed for human participants, with effort being manipulated in terms of, for example, the force to be exerted on a handgrip or the number of clicks on a mouse (Treadway et al., 2009; Pre-vost et al., 2010). The reward can come in the form of food or tokens/credits, but typically for human studies is monetary. By adjusting the offers given during the dual-alternative procedure based on participant choices in an adaptive staircase design, an indifference point can be reached whereby the participant is impartial to the two choices given (Klein-Flugge et al., 2015; Le Bouc et al., 2016; Westbrook et al., 2013). Typically, the value of the low effort/low reward option is held constant, while the high effort/high reward option is titrated incrementally as a function of participants' responses. Therefore, if the high effort option is chosen, the participants will be presented with an offer on a subsequent trial that either requires even greater effort or offers less reward. For example, Ostaszewski et al. (2013) define effort as the lowest amount of effortless monetary reward that a participant chooses over a higher reward amount that requires effort. Similarly, Lopez-Gamundi and Wardle (2018) use the percentage of hard tasks chosen when faced with several probability-based options.

One prominent reward-based decision-making measure of effort that explicitly requires participants to consider relative costs and benefits is the EDT paradigm (Westbrook, et al., 2013). The EDT is a 'choice experiment' designed to find a participant's indifference point. To achieve this goal, participants are offered a series of choices between completing a high-load task for more reward or a low-load task for less reward, with the reward amount for the hard task being adjusted (Figure 4; Westbrook & Braver, 2015). The subjective points of indifference are then used to calculate each individual's effort levels in terms of an SV. For example, if a participant were indifferent between $2 for a harder task, and $1.20 for an easier task, the subjective cost of the harder relative to the easy task is 80c, and so the SV of the $2 reward for completing the hard task is $1.20. The indifference point is useful in understanding effort, as it makes two different monetary rewards of equal SV, when accounting for the costs and payoff associated with each task.

Figure 4

The EDT Titration of Offers With a $2 Base Reward Amount from Westbrook and Braver (2015). Permission Was Granted for Use of This Figure from Cognitive, Affective, & Behavioral Neuroscience



A key use for indifference points is that they are suitable for computational modelling to enable a more precise analysis than typical linear models (Białaszek et al., 2022). For example, discounting models (Myerson et al., 2017) describe how the value of an outcome changes as a function of the effort by quantifying the ‘shape’ of the underlying preference function, based on various difficulty levels of a task. There are four main types of non-linear functions that typically are used to model indifference points. These are hyperbolic (Mazur, 1987), parabolic (Hartmann et al., 2013), exponential (Green & Myerson, 2004), and sigmoidal (Klein-Flügge et al., 2015). However, this is not an exhaustive list, and there are various reparameterisations used to measure effort discounting (Białaszek et al., 2017; Klein-Flügge et al., 2015). While comparisons of discounting models have produced mixed results (Chong et al., 2017; Klein-Flugge et al., 2015; Ostaszewski et al., 2013), having the ability to computationally model the outcome of dual-alternative paradigms is a key strength.

The main benefit of using the EDT is that it measures the participant's inference using SV calculated from two dimensions; participant choices of two task difficulty options and reward magnitude, rather than solely from the manipulation of reward magnitude alone. Including the two and manipulating them systematically is important, as the relationship between effort and reward is complex (Westbrook & Braver, 2015). For example, it has been shown that monetary incentives can have both positive and negative influences on performance (Bonner et al., 2000). In addition, using solely reward relative to choices between hard and easy tasks to modulate effort expenditure requires the researcher to make assumptions regarding what they think is important about a task, which may not necessarily align with the participant's preferences (e.g. boredom could drive a high demand choice, not money). When using two-choice experiments that manipulate both task difficulty and reward magnitude systematically however, it is possible to offer the participants equal amounts of money for harder and easier tasks to test such assumptions. If this assumption is met, it can then be inferred that the calculated SV is chiefly driven by manipulations in the dependant variables, rather than by other more unspecific factors.

Another advantage of the EDT is that it can easily be adapted to different tasks and reward types. Having the ability to measure and compare different types of effort within one overarching framework may also be particularly valuable in predicting real-world outcomes, given that many modern jobs require cognitive rather than physical effort. For example, the prominent manifestation of the EDT is the COG-ED (Westbrook et al., 2013), during which participants make choices between easier and more difficult versions of a WM task (n-back) and have to complete consequential trials on a lottery-based system (e.g., one of their choices is chosen at the end of a section to complete). A key strength of the COG-ED paradigm is that working memory ability is measured, and so can be controlled for during analysis. It is also trivial for future designs to control for the confounding influence of ability further by proactively adjusting effort offers (e.g., by offering increasing n) based on performance during training.

Recent studies have shown the COG-ED to have good test-retest reliability (Mækelæ et al., 2023). Using the COG-ED set up, Westbrook and colleagues also found willingness to expend cognitive effort to be trait-like, as it significantly positively correlated with NFC, a previously discussed and well-established self-report measure of daily engagement with and enjoyment of cognitively demanding tasks (Cacioppo & Petty, 1982). Therefore, greater willingness to repeat the harder version of the n-back task for more reward predicted reduced trait engagement with cognitively demanding tasks. They also found that the COG-ED willingness predicted NFC scores, whereas scores for the NASA Task Load Index (Hart & Staveland, 1988) previously discussed did not, supporting the idea that behavioural economic preferences as measured through dual alternative measures such as the COG-ED may be a more sensitive measure of effort than self-report measures. Besides NFC, the COG-ED has also been shown to have relevance in psychopathology. By using the COG-ED framework to quantify SVs as a global measure of cognitive effort, researchers have been able to examine risky decision-making (Apps et al., 2015), psychosis (Chang et al., 2019), effort-cost computations in schizophrenia (Culbreth et al., 2016), depression (Westbrook et al., 2022), and the role of dopamine in decision-making (Westbrook & Braver, 2016).

One drawback with the COG-ED is that it is yet to be fully understood how SVs relate to reward amounts. For example, sometimes SV significantly differs by hard task base offer amounts (Westbrook et al., 2020), but then at other times does not (Culbreth et al., 2019). Part of this issue is that it is difficult to reliably estimate how cost sensitive someone is (Musslick, et al., 2019). For example, it is likely that people have different cost sensitivity, demands of task, capacity for engagement etc., which all relate in different ways to choice behaviour. Nevertheless, more research is required varying the reward amount pairings to perhaps account for reward sensitivity, prior to asking the effort-based questions.

A further drawback is that the COG-ED entails asking participants to make a series of hypothetical decisions relating to tasks that are only in part related to a later realisation of effort (Westbrook et al., 2013). Specifically, the COG-ED, like many other effort-based decision tasks in humans, involves asking participants to make hypothetical, or quasi-real, choices. Therefore, participants either imagine their efforts (Ostaszewski et al., 2013), or practice the relevant task prior to choices and perform only a subset of choices made (Lopez-Gamundi & Wardle, 2018; Westbrook et al., 2013). During the second 'lottery-based' system, participants make decisions with the knowledge that they will only have to complete a randomly generated subset of all the choices that they make. This is done because the use of real rewards limits the magnitude of reward and the size of the effort condition tasks required to achieve reward (Madden et al., 2004). For example, it would not be feasible or ethical to repeatedly ask a participant to climb 100 flights of stairs for a small reward, nor to pay participants for every choice they make. Hypothetical tasks also are time efficient and mean that multiple possible choices can be assessed in a single testing session. However, while it is hypothesised that participants should behave as if every selected outcome is real, given that each choice has an equal chance of being selected for them to complete at the end of the experiment (Madden et al., 2004), little research has been conducted systematically comparing these types of designs, to assess for differences in decision-making.

The debate surrounding consequentiality stems from a concern that the decisions of an individual making hypothetical decisions may not by synonymous with same decisions for real ones (Madden et al., 2004). This is because, contrary to the delay discounting literature where time is one-dimensional, effort is a multifaceted construct (Ostaszewski et al., 2013). As a result of such concerns, researchers have designed experiments in which real and hypothetical outcomes using the discounting paradigm are compared, with the aim of internally validating hypothetical and quasi-real procedures.

Some studies have shown that using virtual compared to real reward make little difference on effort production (Bickel et al., 2009; Madden et al., 2004). However, in a within-subjects design study investigating the effects of real versus hypothetical rewards on effort discounting, Malesza (2019) asked 142 participants to make choices between an effortless amount of money, or 100 Euros after putting in an effort. Importantly, over two testing sessions, participants would either make hypothetical decisions, or consequential ones, where they were told that one of their choices would be randomly selected to complete. They found that hypothetical discounting mirrored potentially real outcomes for low, medium, and high physical effort levels. They did however find order effects, with potentially real being second showing significantly greater discounting. They also found that your first choice for the consequential, but not the hypothetical, condition impacted future choices. Specifically, you re-produce your response. They looked to see if lack of difference between hypothetical and real holds if repeated ANOVA is only carried out on participants for which hypothetical preceded the real. They found no significant effect of task type. Other studies also suggest that differences exist (Camerer & Mobbs, 2017; Xu et al., 2016). Future studies are required to directly compare real, quasi-real, and hypothetical effort-based decisions, ideally within and between groups, by either comparing groups, or using a continuous scale from real to fully hypothetical. This would inform EVC and could show that the consequentiality is a confound.

An alternative measure that avoids this potential confound by using consequential trials is the EEfRT (Treadway, et al., 2009). During the EEfRT, participants are asked to choose between pressing a lever thirty times with their dominant hand (Easy Task) for lower reward and pressing it one hundred times with their non-dominant pinky finger (Hard Task) for higher reward. Participants not only make their decisions based upon reward amounts and task difficulty, but also while considering 'probability of win' (either 12%, 50% or 88%). For example, a participant may be asked to choose between the easier task for $1 dollar or the harder task for $2, with an 88% chance of them being paid upon successful completion of a subsequent consequential trial. Therefore, as well as considering likelihood of reward alongside task difficulty and reward, participants are also required to immediately act upon their choices and complete consequential trials.

There are many attractive properties to the EEfRT. Firstly, like the COG-ED, the EEfRT requires no special equipment. Secondly, it has good translational validity, as it parallels well established physical effort tasks used with animals (Koch et al., 2000). Thirdly, like the SV from the COG-ED, this measure has been used to characterize effort-based decision-making in several patient populations. For example, willingness to choose the high-effort/high-reward option has been shown to be lower in those with major depressive disorder compared to healthy controls (Treadway et al., 2012), lower in patients with schizophrenia compared to demographically matched controls (Gold et al., 2015), associated with lower depression severity and anhedonic symptomology (Barch et al., 2014), worse community functioning in individuals with schizophrenia (Barch et al., 2014), and be greater in patients with autism spectrum disorder (Damiano et al., 2012).

As well as clinical relevance, performance on the EEfRT has also begun to be used to understand the role of dopamine in decision-making. For example, Wardle et al. (2011) showed that dopaminergic stimulants increase willingness to expend effort on this task. Another study by Treadway et al. (2012) shows that greater willingness to complete the hard task option during the EEfRT is related to better dopaminergic functioning in healthy controls. The final main positive of the EEfRT is that it has been adapted to measure effort types other than physical effort. In a recent study by Lopez-Gamundi and Wardle (2018), the EEfRT was adapted to measure cognitive effort. During the cognitive version, the C-EEfRT, participants view a series of numbers ranging from 1-4 and 6-9 presented one at a time. If the number displayed is blue, the participant is asked to indicate whether the number is odd or even. If the number is yellow, the participants need to respond whether the number is above or below 5. The participants are asked to choose between completing hard and easy versions of this task just as they would otherwise do in the EEfRT. This has also recently been replicated with an attentional version of the EEfRT, where discounting of reward was shown to be similar to the original button pressing version (Lim et al., 2023). Overall, the EEfRT is a well-validated translational behavioural measure of willingness to exert effort.

In a recent study where both the COG-ED and EEfRT were used in the same group of participants found the COG-ED, but not the EEfRT, to be significantly predictive of participants self-reported daily physical demands (Culbreth et al., 2019). This is initially surprising given that participants in the EEfRT are required to complete consequential trials, which you might expect would make responses less abstract and more ecologically valid. However, another recent study by Renz et al. (2022) also found the EEfRT not to relate to self-report and observer-rated measures of amotivation. Such results may be because the EEfRT requires participants to also consider the probability that they will be rewarded when making their decisions. Therefore, decisions could be based on likelihood of reward, reward magnitude, skill, or other factors, which may not be related to their choice to engage in physically demanding daily activities such as household chores. Although initial comparisons seem to favour the ecological validity of the COG-ED, more research is required to comprehensively compare these measures.

Both the COG-ED and EEfRT are explicit dual-alternative task, where the participants are asked to directly make effort-based decisions between a high or low effort task. However, a drawback with both is that they may be subject to secondary demand characteristics, whereby participants may make choices according to what they think is expected of them, or what the experimenter expects of them. To avoid both the issue of consequentiality and demand characteristics, Bustamante et al. (2023) developed the Effort Foraging Task (EFT). In this task, participants learn about the decision landscape (i.e., the reward rate and effort costs) through experience, and make choices based on these estimations. During the EFT, participants make sequential decisions whether to continue harvesting a depleting patch, or whether to travel to another area to forage, at the immediate cost of completing an effortful task and the time taken to do so. The task was either cognitive (a multi-source interference task), or physical (button pressing). The participants exit threshold represents the amount of reward the participant expects to receive by travelling to a new patch. Exit thresholds have been shown to be sensitive to cognitive and physical effort demands (e.g., between easy and difficulty levels), thus allowing the perceived effort cost to be quantified. Such tasks have been shown to have ecological validity in, for example, being able to distinguish between Parkinson’s patients with and without dopamine medication (Constantino et al., 2017).

Importantly, the EFT allows for a preference for lesser rewarding higher effort tasks, which neither the COG-ED nor EEfRT do. For example, the staircase procedure used in the COG-ED (Westbrook et al., 2013) is asymptotic to its upper and lower bounds, which are typically 0 and a variable monetary amount. This is in line with other measures that do not allow for effortful outcomes to exceed effortless options (Białaszek et al., 2017) and rely on the assumption that choices are made to minimise effort. However, given that effort can also be at times sought out rather than avoided (as discussed in Chapter One; Inzlicht et al., 2018; Shenhav et al., 2017), it may be relevant for measures to account for such instances. When comparing exit threshold for high versus low difficulty trials, Bustamante et al., (2023) found evidence for just this instance. Specifically, they found effort-seeking, rather than effort-avoidance, in a minority of participants. This shortcoming can be overcome in the COG-ED and EEfRT rather trivially by allowing a definition of upper and lower limits, a step size, and a minimum step size, making it possible for the SV to be negative (Klein-Flügge et al., 2015). For example, Embrey et al. (2023) adapted the COG-ED task (Westbrook et al., 2013) to allow for participants to choose a greater effort option for the same reward (e.g., $2 for hard or easy), and converted indifference points for participants that preferred the more difficult option. Another approach has been to use Bayesian adaptive design optimisation, where the stimuli are not predefined, but instead are computed in line with objectives, such as the estimation of unknown model parameters (Ahn et al., 2020).

While the EFT task solves the issue of demand characteristics and allows for effort-seeking, the decisions made, like during the COG-ED and EEfRT can be confounded by ability. This is problematic because in EVC model simulations (Musslick et al., 2019), where factors other than effort costs, such as skill and reward sensitivity contribute to estimations of value. Therefore, choices away from a harder version of a task can appear to be effort avoidance, when it is in fact driven by the participants ability and/or their perception of incentives. For example, in the n-back working memory task used during the COG-ED (Westbrook et al., 2013), the levels become exponentially more difficult beyond n = 2, due to the demands placed on working memory (Callicott et al., 1999). As reported by the researchers, success rates in healthy controls decreased sharply after n =2 (Westbrook et al., 2013). This is also true for the EEfRT, where button pressing can also be influenced by the participants ability (in terms of their physical strength), as well as for the EFT, where effort has been shown to correlate with error (Bustamante et al., 2023).

To attempt to minimise ability as a confound, some measures provide alternative offers to participants that are a between zero and one hundred percent of their maximum ability. For example, in the accept/reject apple task used by Chong and colleagues (2015), participants are tasked with accumulating as many cartoon apples as possible based on the combinations of reward and effort presented, where effort is operationalised as hand grip indexed against the participants maximum hand grip strength. Doing so normalises the difficulty of each effort level across individuals. Using this method, they were able to show that participants with Parkinson's disease had lower indifference points, regardless of medication status. An interesting variant of the above paradigm can be obtained by indexing the payoff not on peak force but on effort duration (Meyniel et al., 2013). Effort production in this task can be interpreted as resulting from decisions about the durations of effort and rest periods, which in principle can take any value from zero to trial length.

Other measures circumvent the issue of ability by requiring their participants to complete training trails in which they are required to reach certain thresholds. For example, during the Cognitive Effort Motivation Task (CEMT; Ang et al., 2022) participants make choices between a fixed low reward for completing an easier version of a working memory task (less items), or a higher reward for a variable higher effort requirement (effort measured as proportion of high reward high effort task chosen). The decisions made are consequential, such that after each decision they are required to remember the position of the chosen number of squares in 6x6 grid. They then indicate whether a target appeared in that location during the previous phase. Importantly, prior to make these decisions, each participant is required to complete a learning phase in which they are required to reach 80% correct before beginning, with failure to reach that threshold leading them to completing the task with a 5x5 grid instead. Despite the promise of the CEMT, much more research is required to validate it.

Summary

To conclude, effort-based decision measures currently represent the leading measures of effort. Notably, the COG-ED (Westbrook & Braver, 2015), EEfRT (Treadway et al., 2009), Effort Foraging Task (Bustamante et al., 2023), Apple Gathering Task (Chong et al., 2015), and the CEMT (Ang et al., 2022) represent the most prominent. Key aspects of consequentiality, demand characteristics and confounds of ability have been discussed. Below is a summary of the previous section on effort-based decision tasks (Table 1). While much more research is needed into how effort willingness looks for a wider range of tasks, e.g., typical everyday activities, or enjoyable activities, and the closeness to which estimations of value during decision-making map onto actual engagement, choice behaviour tests currently represent the leading way in which effort is measured, and are arguable most powerful when used in combination with other measures, such as questionnaires (Pessiglione et al., 2018) and brain imaging (Westbrook & Braver, 2015).

Table 1

Summary of Effort-Based Decision-Making Tasks

Measure	Details	Strengths	Weaknesses
Accept/Reject Apple Task (Chong et al., 2015)	Accept/decline offers for higher reward for greater % of maximum grip strength or less reward for lower %. Effort measured as indifference point (50% acceptance).	Selections based on maximum force. Clinical relevance.	Could be confounded by fatigue/reliance on physical ability.
Cognitive Effort Motivation Task (Ang et al., 2022)	Learning phase followed by decisions between fixed low reward for completing an easier version of a WM grid task (less items), or a higher reward for a variable harder task. Measures effort as proportion of hard task choice.	Consequential decisions. Accounts for ability.	Demand characteristics. Requires further replication and validation.
Cognitive Effort Discounting Task (Westbrook & Braver, 2015)	Fixed reward for harder n-back level or variable amount for easier n-back. Small number of lottery-based consequential trials after decisions. Measures effort using indifference points (end value of staircase procedure).	Lottery system of reward. Flexible. Clinical and real-world relevance. Test-retest reliability.	Do not allow for SV to go to zero or below. Large difficulty jumps between levels. Demand characteristics. Ability not controlled for.
Effort Expenditure for Rewards Task (Treadway et al., 2009)	Number of button presses, reward amount and probability of reward varied. Measures effort as ratio of hard task chosen.	Consequential decisions. Clinical relevance.	Do not allow for SV to go to zero or below. Demand characteristics. Ability not controlled for. Possible fatigue effects.
Effort Foraging Task (Bustamante et al., 2023)	Two types of effort (button press and interference task). Continue to receive diminishing reward or switch at the cost of completing an effortful task Measures effort as exit threshold.	The cost of effort can be negative. Two types of effort used. Indirect measure. Consequential decisions.	Choices could be influenced by time costs as well as the effort. Ability not controlled for.

With the above methodological information above in mind, Chapters Three and Four utilise both dual-alternative and self-report measures. Firstly, an adapted version of the COG-ED (Westbrook et al., 2013) was used whereby the n-back was replaced with other effort tasks. It was also chosen due to its test-retest reliability (Mækelæ et al., 2023), which was particularly important given that effort was predominantly to be compared within-subjects. The influence of ability was mitigated by adjusting the offers based on performance during training, based on other studies using different effort measures (Ang et al., 2022). Finally, participants were allowed to make their effort choices away from the experimenter's gaze to reduce demand characteristics. The full procedure will be discussed in the studies to come. In each of the following two chapters, I also used self-report, as it allowed us to measure effort for a range of activities and increase the generalisability of our findings.

Outstanding Methodological Questions

A potential methodological confound with current choice behaviour measures, as highlighted by Embrey et al. (2023), is that effort measures typically require rule implementation and maintained attention. For example, in the n-back task, strategy (i.e., maintaining a string of previous letters in working memory) and keeping up with the rules (i.e., checking if the current symbol matches the symbol from n turns ago), are well defined parameters to success. In a study investigating the impact of financial reward on performance between rule-implementation tasks and those requiring rule/strategy-based discovery, Osborn et al. (2022) found that while incentives can drive decision-making in relation to categorisation tasks that require rule-implementation (e.g., Shepard et al., 1961), they do not when the rules are unclear. This is in line with findings from Enke et al. (2023), who show that incentives do not influence effort when participants are unable to solve the problem in front of them. Such findings contrast with other tasks, such as counting and button pressing, where incentives did drive effort (Caplin et al., 2020; DellaVigna & Pope, 2018). Task type also seems to influence the phenomenology of effort. For example, people report differences in the sense of effort experienced by mental tasks depending on whether they require attending (e.g., counting the drips of a tap) compared to assessing (e.g., weighing up which item to purchase; Robinson & Morsella, 2014). While the above findings do not necessarily imply exerting cognitive effort in abstract, problem-solving tasks is less (or more) aversive than attentionally demanding, rule-implementation tasks, it does suggest the type of thinking required to solve them is qualitatively different. Such qualitative differences may explain why recent studies find weak relationships between effort measures Mækelæ et al (2023).

Given that these two 'types' of measures seem to capture different aspects of effort willingness, to what extent can current theories of mental effort generalise beyond those observed in the lab where the type of cognitive demands are largely homogenous? Beyond rule implementation and attention, demanding tasks in the real world also differ greatly, and effort measures should reflect this. For example, the parameters for success move well beyond rule implementation and attention in something like chess, where no single strategy guarantees success. Daily activities such as washing up or cleaning seem likely to be governed by different rules than those in the lab. Much more research is needed by comparing multiple effort measures in one sample and comparing them, in follow up to studies such as the one by Mækelæ et al (2023).

In a similar vein, another methodological question relates to instances in which effort willingness is influenced by cognitive emotional dimensions such as interest/boredom, flow/struggle, calm/stress. As effort has classically been viewed as a cost, measures of effort have relied on participants choosing between tasks that are more or less aversive. However, in the real-world people do not always choose between more or less aversive tasks. For example, Bench and Lench (2019) find that participants in high-boredom conditions are more likely to sensation seek than those in low-boredom alternatives. In some instances, participants are even willing to seek negative sensations (e.g., electric shocks, disgusting images) to alleviate boredom (Nederkoorn et al., 2016). Similarly, recent work by Wu, et al. (2023) shows that people would rather complete mathematical working-memory problems than a boring alternative such as doing nothing. In these cases, the cost of mental effort is not necessarily diminished, but rather the cost of boredom is greater than the cost associated with task engagement.

More adaptations to current methods are required, perhaps by using appetitive rather than aversive stimuli, and by offering participants options across task options.

Finally, effort measures currently give snapshot of effort willingness. However, studies show that effort can change over time. For example, studies show that SV can be influenced by recent effort-based choices (Vinckier et al., 2019), and even update estimations of cost during task execution (Nagase et al., 2022). A recent study by Lin et al (2024) shows that effort willingness can be improved following reward for effort, even for unrelated tasks in the absence of external reward. Such studies suggest that perhaps that effort willingness should be measured not only in its level (e.g., high versus low willingness), but also in its flexibility to change over time. It would be interesting to have participants go through the paradigm developed by Lin and colleagues with a view to assess the relationship between changes in starting and end effort willingness and their relationship to NFC. It may be that effort willingness flexibility is especially predictive of outcomes over time, though this requires further exploration.

How Effort is Measured in the Current Thesis

Effort is defined in the current thesis as the willingness to endure costs associated with task engagement. While the definition of effort is objective, effort as a construct is abstract and so is difficult to directly observe. To objectively measure an individual's effort willingness, one could use brain imaging to assess patterns of activation for areas in the brain already shown to be involved in the SV estimation, such as the vmPFC (Lopez-Gamundi et al., 2021). Specifically, would the vmPFC activate to a lesser extent on those with high effort willingness? Alternatively, is it that the activation is the same for those cost areas, but the way the information is synthesised is different? For example, does activation in an area such as the dorsal anterior cingulate cortex, which has been shown to activate particularly during close comparisons of two options (Westbrook et al., 2019), differ for someone who is aware of the cost of a certain behaviour, and decides to do it anyway, compared to someone who perceives the cost as greater and does not? Such a difference would support the notion that those with high effort willingness may be aware of the costs of task engagement but discount the costs after the fact.

As the research focus of the present thesis is on explaining decision-making in different contexts, rather than how effort willingness is reflected in the brain, subjective proxies are instead used to estimate effort willingness in Chapters Three and Four. As has been discussed in Chapter Two, effort is typically measured subjectively using self-report (e.g., Cacioppo & Petty, 1982; Hart & Staveland, 1988) or through choice behaviour during decision-making tasks (e.g., Ang et al., 2022; Chong et al., 2015; Westbrook & Braver, 2015). Here, we use both and triangulate the results from both to better understand effort willingness in different contexts. We also correlate these effort measures to established measures, notably grit and NFC.

One option for measuring participants effort willingness level using self-report could have been to design and validate an ‘Effort Willingness Questionnaire’ or ‘Effort Scale’. Such a measure would likely have included questions such as ‘I am generally more willing to do more difficult tasks than my peers’, with participants responding on a Likert-style scale from Strongly Agree to Strongly Disagree. Asking participants to respond to statements in this way is common for other constructs, such as in the grit, anxiety and NFC (Cacioppo & Petty, 1982; Duckworth et al., 2007; Spitzer et al., 2006). However, while a willingness-to-exert-effort questionnaire could have been developed and validated, this approach was not taken, as the primary interest for the research team was on understanding the cognitive processes driving effort-based decision making across different contexts. Therefore, rather than trying to quantify a person’s single effort willingness value and then assessing how it relates to other constructs of interest or other metrics, the focus was instead primarily on how effort willingness relates in the individual across different contexts. Thus, when making cognitive appraisals of how costly a task is, to what extent is this choice context dependant, versus domain general? Also, in addition to effort willingness, what other aspects explain variation in effort-based decisions? Such questions will be more formally discussed in the following chapters of this thesis.

Rather than asking participants to respond to general statements, Studies 2a and 2b use participants' self-reported perceptions of the effort exerted in specific tasks as an indirect measure of effort. These ratings provide an introspective measure of perceived effort. While we are expecting variation in effort level across tasks, due to aspects that influence task engagement such as ability, reward and perceived efficacy (Shenhav et al., 2013), the question is whether estimations correlate within individuals. We assume that if effort willingness drives perceptions of cost regardless of the task, that this should be reflected in their effort exertion in everyday life. Asking about effort for everyday tasks is advantageous as it allows us to gather many effort values for many different contexts, increasing generalisability of findings compared to studies using specific lab measures that participants are unlikely to have experienced before (e.g., the n-back; Westbrook et al., 2013).

In addition to self-reported effort of daily activities, effort is also measured in Studies One and Three using dual-alternative decision-making tests. A previously discussed, during these tasks participants choose between two competing options with varying costs and rewards. Such tasks yield objective patterns of behaviour, even though they derive from participants subjective choice. Therefore, if a participant continues to choose easier options across many contexts despite smaller rewards, we can interpret this as lower effort willingness. The SV generated from these decisions serves as a proxy measure of effort willingness, as participants with high effort willingness should choose harder tasks for higher rewards, compared to easier tasks with lower rewards, assuming all else is equal. This is because their higher effort willingness reduces the subjective cost of the candidate task before them, thereby increasing their SV. By examining these decisions across multiple contexts, we can evaluate whether choices remain consistent within individuals.

Here, we do not correlate these two types of measures within-subjects, but instead use both and triangulate the findings to get an overall sense of how effort willingness influences decisions in different contexts. Studies using daily life estimations of effort and lab-based effort-based decision making have shown significant correlations between the two. For example, Westbrook and colleagues

(2020) found real-world effort as measured using ecological momentary assessments (EMA) to relate to participant's willingness to exert effort for rewards in the lab. Therefore, we used both measurement types to examine effort willingness. The self-reports provide subjective insight into effort perceptions, while the decision-making tasks capture behavioural tendencies. Both methods allow for a better understanding of how effort willingness influences decision-making in different contexts.

CHAPTER THREE: HOW DOES AN INDIVIDUAL'S WILLINGNESS TO EXERT EFFORT ON ONE TASK RELATE TO THEIR WILLINGNESS WITHIN AND ACROSS DOMAINS?

Chapter Introduction

Leading theories of motivation stipulate that decision-making is determined by a cost-benefit analysis. Effort is typically implicated in the cost component of these models. However, it remains unclear whether effort influences decisions uniformly across all types of tasks, or whether it does particularly more or less so for cognitive versus physical tasks. Given recent developments in how effort can be measured using effort discounting task paradigms, it is now possible to compare the 'cost' of effort across different tasks within a sample. The study was conducted shortly after Covid-19 restrictions were lifted, meaning that social distancing procedures were in place as specifically instructed by the UEA psychology department. The study investigates how an individual's willingness to expend effort in one domain (i.e. physical) relates to their willingness in another (e.g. cognitive), when controlling for the potential confound of ability. Rather than asking participants to make choices between repeating different versions of either a cognitive or physical task e.g., n-back or button lever press task, we wanted to compare effort-based choices within-subjects across physical, cognitive, and dual tasks. The current study was therefore designed so that the participants repeated a streamlined version of the EDT procedure in relation to each task within-subjects.

Without repeating what is to come below, it is worth noting that I propose three models that likely describe the relationship between effort types. The first model reflects domain specificity, where we expect dissociation in effort willingness between the cognitive and physical tasks, with little impact on the dual task, nor trait-related measures. The second model reflects effort as amodal, where there is little distinction between tasks, with willingness lowest for the dual task. The third model is that effort is tied to specific abilities within a domain, such that effort ties to ability for certain tasks within a domain. Also contained is a follow-up study of self-reported ratings of effort exertion in daily life, where factor analyses is used to again test whether effort can be understood in terms of domain, when controlling for aspects such as competence and experience. This data is reanalysed in Chapter Four Study 2b - Part Two, along with additional data collected from the same participants at the same time.

Studies assessing the domain specificity of effort are needed, as the current literature is undecided as to whether effort willingness stems from a domain general or domain specific system. Neuroimaging research shows overlap in brain areas involved in cognitive and physical effort (Chong et al., 2017). For example, Schmidt et al. (2012) found similar neural structures responsible for a both numerical comparison task (cognitive effort) and a hand grip task (physical effort). Behavioural studies in typical populations also show that both types of effort costs correlate within individuals (Białaszek et al., 2017; Bustamante et al., 2023; Westbrook et al., 2013), and that cognitive fatigue impacts physical effort (Giboin & Wolff, 2019; Marcora et al., 2009). Clinically, studies have also shown lack of effort across cognitive and physical tasks for monetary reward within subjects (Reddy et al., 2015).

However, studies have shown seemingly different cost functions for cognitive versus physical effort (Chong et al., 2017), as well as distinct patterns of effort for cognitive versus physical tasks as a function of experience (Chong et al., 2018). Studies also show differential impacts of dopamine antagonists across cognitive versus physical effort discounting (Hosking et al., 2015). A recent meta-analysis by Holgado et al. (2020) assessing the impact of cognitive fatigue on physical performance was also inconclusive. Additionally, few studies have used the same effort measure with cognitive and physical tasks (Bustamante et al., 2023). Understanding the domain specificity of effort could encourage the integration of largely separate literatures on cognitive and physical effort, as play a role in shaping interventions with primarily clinical, educational, and industrial application. Therefore, this topic requires further investigation.

In sum, we investigate the degree of domain-specificity versus domain-generality of effort. Specifically, whether the common distinction between mental and physical effort holds weight. We do this by measuring effort for multiple in-lab tasks from each domain. We also test the effort divide, as well as other factors that might influence effort exertion, more broadly by collecting self-report data about an even greater number of tasks from a large online sample. These are understudied areas and addressing them will help us to learn whether the often separate cognitive and physical effort literatures can be interpreted together to improve our ability to understand effort cost estimations in various contexts.

All data collection, wrangling and analyses were performed by myself for all the studies presented in this thesis herein, except for the PCA and cluster analysis from Study 1 which was completed by Sara Bengtsson.

Abstract

A distinction is typically made between cognitive and physical tasks in the literature regarding cost-benefit estimations of effort expenditure. While studies typically separate ‘mental effort’ from ‘physical effort’, a moderate relationship in effort discounting is typically seen when directly comparing the two. In Study 1 we include more than one task within a domain, and a dual task, to investigate domain-specificity. In addition, we explore amodal effort processes by General Intelligence, Grit, Anxiety, and Pain threshold. 93 participants estimated their willingness to repeat each of four tasks: a musical and a non-musical discrimination task, a physical task, and a dual task, using an effort discounting paradigm, on performance-adapted choices. A principal component analysis revealed a single source of effort estimations, and a cluster analysis did not distinguish domain. The dual task typically generated lower SVs of effort. General intelligence explained 7% of the variance of effort. Instead, we found support for effort being related to task experience and ability in that musical experience influenced task-specific effort through the mediator musical task-performance. This finding is further supported by the results of Study 2, where we performed confirmatory factor analyses on two separate online samples of effort ratings of 8 everyday activities (*N* = 381, *N* = 348), as well as an additional online sample (*N* = 48) who rated ten other activities, rated by participants as being distinctly either cognitive or physical in nature. In both analyses we find poor support for dividing effort ratings according to whether the task is cognitive or physical. We argue therefore that dividing effort into either ‘cognitive’ or ‘physical’ domains is not a useful approach, and that individual differences in effort are likely best explained due to task-specific state and trait-like factors, irrespective of domain.

Introduction

We are all familiar with the sense that others put in more effort than ourselves at times when, for example, running for a bus, revising for an exam, or practicing a musical instrument. Why people are sometimes willing to exert effort, and sometimes not, is valuable to understand in order to predict task engagement and to design interventions. We know that people tend to exert more effort the greater monetary incentive there is (Schmidt et al., 2012) and that the greater the effort, the more the value of reward is discounted (Klein-Flügge et al., 2015). Fatigue is another aspect that can drive preferences for low-cost/low reward options over higher cost/higher reward alternatives (Iodice et al., 2017; Lopez-Gamundi & Wardle, 2018), as is pain (Vogel et al., 2020). Such findings align with the notion that effort is state-like and controllable, where the choice to engage is influenced by the costs relative to the gains (Kool & Botvinick, 2014). However, this does not exclude the possibility that trait-like aspects may influence judgements as to the expected value of effort. A twin study on the etiology of grit, which is a measure characterized predominantly by the extended sustainment of effort, estimated grit to be over 30% heritable (Rimfeld et al., 2016), and stable over time (Duckworth, 2016; Eskreis-Winkler et al., 2014). Likewise, the Processing Efficiency Theory (Eysenck & Calvo, 1992) proposes that anxiety mediates resources directed to effort, which is reflected in studies showing that individuals high in state or trait anxiety tend to put in more effort in high stake trials than less anxious individuals (Berchio et al., 2019; Putwain & Symes, 2018). Also, anxious individuals tend to prefer safer, lower effort options to reduce the risk of an uncertain outcome (Charpentier et al., 2017). General cognitive ability (intelligence), as well as heritable musical ability, are other aspects contributing to the willingness to exercise long-term effort, in this case musical training (Manzano & Ullén, 2021; Mosing et al., 2019).

Two aspects of effort; the external reward situation and the more trait-like aspects, such as the perceived ability to perform well, are nicely integrated in the Expected value of control (EVC) model (Shenhav et al., 2013), where data shows that control based on reward likelihood is processed in separate neural pathways than control based on estimates of efficacy (Frömer et al., 2021). The dorsal anterior cingulate cortex, the ventromedial prefrontal cortex and ventral striatum, have been outlined as key structures in monitoring information about reward benefits and effort costs gathered from separate brain regions, to assist in calibrating the direction and intensity of effort based on maximum expected future reward (Schmidt et al., 2012; Westbrook et al., 2019). Recently, effort has been conceptualized as a cost function that plays an role in optimizing behaviour, by driving individuals to find the critical amount and direction of control allocation for which they can balance potential task rewards and costs, while remaining flexible to other potentially rewarding tasks, on an ongoing basis (Westbook, 2021).

Theoretically, effort is understood to influence control allocation for any behaviour requiring cognitive control (Shenhav et al., 2013). This includes what could be described as tasks in the 'physical' domain, which are thought to require control to maintain intensity for the duration of the task (André et al., 2019). Given that effort is considered a multifaceted construct, it has been operationalized in a number of ways e.g., button press, hand grip, n-back, demand selection (Klein-Flügge et al., 2015; Kool et al., 2010; Lopez-Gamundi & Wardle, 2018; Park et al., 2017; Westbrook & Braver, 2015). Within these tasks, effort is commonly measured in terms of SVs, which quantify the value of an explicit reward given the effort required to reach it. For example, if a participant is indifferent between repeating a 4-back working memory task for £2 or an easier 2-back for £1.50, it could be said that the 'cost' of the increased effort for the harder task is 50 pence. This means that the SV of the £2 reward given its associated task is £1.50. SVs are therefore sensitive to both rewarding aspects, such as monetary reward, and costs, such as task difficulty (Westbrook et al., 2013).

Using SVs, a number of studies point towards a moderate relationship between the cognitive and physical tasks: Lopez-Gamundi and Wardle (2018) found a moderate relationship between willingness to repeat the two types. Ostaszewski et al. (2013) and Białaszek et al. (2017) found a moderate relationship in the steepness of effort discounting; the extent to which the SV of the reward decreases, as the effort cost required to reach the reward increases. Bustamante et al. (2023) found a moderate positive relationship between cognitive and physical high effort cost; the willingness to accept diminishing rewards to avoid effort exertion. Other studies looking at effort exertion find moderate to substantial correlations, for example, across English, Math and Science subjects within high school student populations (Green et al., 2007; Marsh et al., 2001; Trautwein et al., 2006). This is supported by the brain imaging study of Schmidt et al. (2012), which found that while cognitive and physical task demands activate separate brain areas, neural signals from the ventral striatum are commonly sent to these areas with information on discrepancy between reward and required effort. In other words, the value of reward estimation is driven by a common system, irrespective of if effort is exerted on a cognitive or a physical task.

However, in behavioural studies where both a cognitive and a physical task have been included, Tran et al. (2021) found a significant difference in the willingness to do the hard version, as opposed to the easy version, of a cognitive and a physical task respectively, and Cormier et al. (2019) in a study on grit, found participants' estimations of long term effort willingness to differ depending on whether the participant considered their efforts towards sports, or school-work, where grit estimations of school work highly correlated with school grades, unlike sport grit. Additionally, while studies looking at Major Depressive Disorder, in an aim to understand anhedonia and motivation, find depression to be associated with reduced willingness to exert physical effort (Cléry-Melin et al., 2011), and increased perceptions of effort during cognitively demanding tasks (Ang et al., 2022), in a systematic review, Horne et al. (2021) found that physical effort was reduced with depression in half of the reviewed studies, with reduced cognitive effort seen in three-quarters of studies. Such findings suggest that there may be a distinction between cognitive and physical effort in underlying processes. However, it should be noted that there were fewer studies on cognitive effort, that the type of task within domain was found to matter, and only one of their 43 reviewed papers included both a cognitive and a physical task. We reach the same conclusion as the authors in that more research is needed to determine if cognitive and physical effort rely on different mechanisms (Horne et al., 2021).

To further complicate matters, studies show that differences in effort between tasks may be driven to a certain extent by individual experience. For example, Chong et al. (2018), found athletes were more willing to exert general physical effort than non-athlete controls, even when adjusting for performance differences. They also found athletes effort discounting for a cognitive task to follow a concave pattern, compared to a convex pattern for non-athletes. Another study by Clay et al. (2022) shows that rewarding effort, rather than performance, during a 15-minute n-back task, led to greater preference for a later unrelated math task compared to a group rewarded for performance. Recently, we have shown that perceived task competence and frequency also relate to perceived effort judgements for a range of everyday activities (Chapter Four). While the mechanisms underlying these differences remain a topic of debate and require further investigation (Chong et al., 2018; Clay et al., 2022), such findings show that the SV of a task depends on a complex interaction between the task, and the individual, which is thought to be updated on an ongoing basis during effort exertion (Nagase et al., 2022; Shenhav et al., 2013).

It should be noted however, that none of the studies looking at effort across domains included alternative tasks to rule out dissociation within each of the cognitive or physical domains. By focusing on only one task in each domain, one runs the risk of biasing the interpretations to be about the cognitive-physical divide, when in fact it may represent the participant's cost-benefit calculation for a particular task. An alternative viewpoint is that there may be a genetic link between effort and specific inherent abilities (Mosing et al., 2014), and thus linked to specific tasks. This argument is supported by a twin modelling study where Mosing et al. found that both basic musical ability, such as melody discrimination, and the amount of music practice (long-term effort) are heritable (40-70%). The authors suggest that this reflects a gene-environment interaction, where individuals seek out activities they have genetic predispositions to be good at, which leads to success, which in turn, provides further incentive to continue practicing.

A way of testing whether there is a domain or task specificity, respectively, is to introduce more than one task of a domain, as well as a dual task. In Study 1, we seek to clarify if there is a cognitive-physical domain divide in effort by having participants perform four tasks; two within the auditory-cognitive domain; a tonal sequence discrimination task (Ullén et al., 2014), and a Zulu and *!Xσυ* click discrimination task (Best et al., 1988; Best, et al., 2003), one in the physical domain; a weighted backpack task (Proffitt et al., 2003), as well as a dual task requiring simultaneous cognitive and physical effort exertion. Zulu and *!Xσu* clicks were used as previous studies find no significant transfer effects from music training to non-native phoneme discrimination (Swaminathan & Schellenberg, 2017), while the tonal sequence discrimination task correlates with musical abilities (Ullén et al., 2014). It is important to note that the weighted backpack task was chosen as the effortful task within the physical domain so that it could be paired with the click task in a dual condition without competing for additional attentional resources. Including a dual task is also particularly useful, as it enables evaluation of the impact on potential shared resources, emphasizing similarities and differences in underlying processes (Koch et al., 2018). In addition, participants undertake tests of General Intelligence, pain threshold, general Grit, and Anxiety. Including a measure of pain tolerance is particularly interesting, given a recent study showing that participants eventually choose to receive pain rather than continuing to complete a working memory task (Vogel et al., 2020). Such a study suggests that pain and effort-related task costs may be estimated in a common evaluation system, though such a notion requires further exploration. Finally, they are asked to rate their musical experience and current level of physical activity, to investigate to what extent experience influences the SV of effort.

Comparing effort willingness between the domains has its difficulties. Fatigue is more likely to lead to rising effort costs for physical tasks as noted by Lopez-Gamundi and Wardle (2018), and task difficulty should be matched between tasks to avoid measures of effort being conflated with measures of limited abilities. This can be done, to a certain extent, by calibrating difficulty levels based on each participant's abilities (Ang et al., 2022; Bengtsson et al., 2009), which is rarely done. Here, we use an Effort Discounting Task to estimate participants' effort for each task (Westbrook et al., 2013), with choices adapted to each participant's performance level. We ask participants to explicitly choose between options until an indifference point is reached. The choices are made between performing an easy version of task A for less money, with a harder version of task A for more money, where the difference in amount of money between the two choices gradually becomes smaller. The indifferent point is then used to operationalize effort in terms of a SV, which represents an individual's preference to avoid a more demanding task in favour of a less demanding task. Measuring effort in this way is thought to reflect the output of an individual's internal cost benefit calculations relating to two demanding task options (Westbrook & Braver, 2015), and is considered a more direct measure of effort, compared to task performance, or process tracing (Thomson & Oppenheimer, 2022).

We investigate three models underlying effort: One possible outcome would reflect domain specificity, where we expect dissociation in the SV of effort between the physical and auditory-cognitive tasks, respectively, with little impact on the Dual task, nor the trait-related measures. A second model suggests that effort is predominantly an amodal, centrally controlled system, where there is little distinction in SV between tasks of different domains, where the SV of effort in the Dual task is lower than any single task, and where general Intelligence, pain sensitivity, Grit, and Anxiety have influence on the SV of effort across tasks. An extension of model 2 holds that effort derives from more specific abilities within a domain, i.e., general ear for music, where ability for the Tonal task and musical practice predict effort, unlike ability for the Zulu click task.

In Study 2a and 2b Part One, we test with factor analyses if the cognitive-physical divide is valid when measuring estimated effort exertion of activities in daily life, such as exercising, cleaning, budgeting, and driving in an unfamiliar environment. In addition, we repeat this analysis in Study 2c but for a more divisive range of tasks, those that are rated by participants as being either 'cognitive' (e.g., Play Chess), or 'physical' (e.g., Dancing) in nature. All three studies are based on online data of participants' ratings of perceived effort exertion. We use factor analyses to assess whether perceived effort ratings for a range of activities would reveal latent variables that could be understood in terms of domain, rather than other task specific factors. In addition, it allowed us to analyse correlations between single activities and each construct, to further understand perceived effort. Finally, using factor analysis reduced our reliance on effort for specific tasks, by summarising our data into specific factors that give an overall sense for how effort is allocated in participants daily life.

Study 1

Method

Sample

93 participants aged 19-58 years (mean 23±7, 66 females), completed the lab-study in return for either £10 or course credits. Those paid money were recruited using social media advertisement (Facebook and WhatsApp), and those paid with course credit were recruited from a student research portal. This reward was the same regardless of EDT choice. The sample was primarily made up of Psychology students (n = 72). The study was approved by the ethical committee in the School of Psychology, University of East Anglia, EAN: 2020-0389-001913.

Due to the inclusion of a Cold Pressor Task, participants were excluded prior to testing in line with previous guidelines (von Baeyer et al., 2005). Vulnerable individuals with respect to Covid-19 were also excluded from taking part. One participant opted out of completing the Dual task. Dual task SV for one participant and the Dual task performance data for three participants were lost due to technical issues. All other data for these participants were included in the analyses, and any missing values were replaced with means. No collected data was excluded.

Materials

Musical Experience and Physical Activity. Participants were asked how many years, and how many hours a week/year they consider themselves to have been actively engaged in musical performance, either with an instrument or singing. A sum-score estimate was created for each participant reflecting total hours played during their lifetime (Bengtsson et al., 2005). Participants were also asked how many hours on an average week they spend purposefully exercising. Both musical experience and physical activity were positively skewed. The data were therefore log-transformed, and univariate analyses were conducted with the transformed and untransformed variables. As both sets of data resulted in the same overall findings, untransformed data were interpreted.

General Intelligence. A 12-item version of Raven's APM (Raven & Court, 1998) was used. Participants were asked to decide which of eight options represents the missing element that completes a pattern while satisfying row and column rules. They were given a maximum of 15 minutes to complete all items, with a 1-minute time warning. The matrices were printed on paper, and responses were recorded in Excel (Microsoft Corporation, Washington). The maximum total score for this task was 12, with one point awarded for each correct item.

Grit. Grit was measured using the 12-item self-report measure (Duckworth et al., 2007). Using a 5-point Likert scale, participants answered statements such as 'I often set a goal but later choose to pursue a different one'. Participants average scores rendered a grit score between one (extremely gritty) and five (not at all gritty). Negative items were reverse scored. A reliability analysis revealed a high level of reliability, with a Cronbach's alpha coefficient of .77. This indicates that the Grit scale has strong inter-item correlation and that the scale is measuring the same underlying construct consistently.

Anxiety. Anxiety was measured using the 20-item state scale of the State Trait Anxiety Inventory (S-STAI, Spielberger, 1983). On a 4-point Likert scale, participants responded to statements such as 'I feel nervous'. All item scores were summed to a total score of between 20 (low anxiety) and 80 (high anxiety), while accounting for reverse scoring of relevant items. A reliability analysis revealed a high level of reliability, with a Cronbach's alpha coefficient of .86.

Pain Tolerance. Participants completed the Cold Pressor Task – using a circulating cooling water bath (Mitchell et al., 2004). The temperature was controlled using a dip cooler and checked using a built-in thermostat and a thermometer. Participants submerged their hand up to forearm in the water to induce pain. They were told to remove the hand when it became too painful, and made aware of the maximum time of 4 minutes (von Baeyer et al., 2005). Measurement indexes were time in water (s) and subjective pain rated on a 10-point Likert scale (1-10, one being minimal pain).

Calculating Effort Scores Using the Discounting Framework. To calculate effort scores for each task, i.e., how willing the participant is to repeat the task, we adapted the methods as described by Westbrook et al. (2013). Participants firstly completed familiarization trials, where they experienced all difficulty levels of a task, before making decisions about whether they want to repeat easier or harder versions of the task for lesser or greater reward respectively. The purpose of having the participants complete familiarization trials was twofold. Firstly, it allowed them to understand what each task entails. Secondly, performance during these trials was used to calibrate the participant's offers in the decision phase. Specifically, their easy task option was the block of trials where they scored a maximum of 80% correct, with the hard task option being the next increased difficulty level. Following familiarization, the experimenter verbally conveyed the offers. In addition, the experimenter placed in front of the participant written labels of the offers. For example, to begin the Effort Discounting Task for the Tonal task where the participant scored 80% correct for the 5 tone difficulty level, the experimenter asked "If I were to ask you to repeat this tonal task that you just completed, but all the trials were of the same difficulty, either always 5 Tones, or always 6 Tones, and were to offer you £1 for the easier alternative or £2 for the harder alternative, which would you choose?" The experimenter then continued by verbally adjusting the offers accordingly until six choices had been made. The base reward amount for the hard condition remained constant at £2. The initial monetary offer for the easy condition was half the offer of the hard (£1). The subsequent offers of the easy condition were determined using a staircase method and deviated with 50%/trial, such that the final 6^{th} offer for the easy condition ranged between 3 pence (easy condition always chosen) and £1.97 (hard condition always chosen). The offer for the easy condition following six choices was taken as the participants' effort score, which quantified the SV of the hard relative to the easy option. Possible SVs therefore ranged from 0.01 (easy always chosen) to 1.99 (hard always chosen), with lower SVs indicating greater discounting, i.e., one is allowing less money to avoid higher effort. The Effort Discounting Task was run using Matlab R2017a.

Perceived Effort and Task Difficulty. The five-item Effort/Importance subscale of the post-experimental Intrinsic Motivation Inventory (Ryan, 1982) was used as a self-report measure of perceived effort. Respondents marked from *Not true at all* to *Very true* on a 7-point Likert scale in response to statements relating to the tasks. Scores were averaged across the statements and used to reflect perceived effort for each task. Participants also rated task difficulty of the different conditions in relation to the other tasks and conditions using a 7-point Likert scale, e.g., *Which is more difficult, the hard tonal task, or the easy backpack task?* We computed average differences ranging from ±6. These ratings were done for the Tonal task, the Zulu click task, and the Backpack task.

Melody discrimination. The tonal discrimination task was taken from the Swedish Musical Discrimination Test (SMDT, Ullén et al., 2014). This task was used because it is a western measure of music ability that correlates with music practice and heritability (Mosing et al., 2014). For both blocks of trials, 18 trials were presented with increasing difficulty; 4-9 tones, each difficulty level had two presentations. Each block took around 7/8 minutes to complete. One of the tones in a sequence pair differed in pitch (e.g., an A might be replaced by a C#). Participants were required to determine which tone differed and responded with a key press. The task was presented using Adobe Flash Player 10.

Non-musical auditory discrimination task. The Zulu click discrimination task was based on the AXB design from Swaminathan and Schellenberg (2017), where A (presented first) and B (presented last) were contrasting speech tokens of different consonants. X, which was presented between A and B, was always a non-identical token from the same category as A (half of the trials) or B (the other half). Participants decided whether A or B matched X. Thus, the task requires phoneme discrimination and matching. The speech tokens used were voiceless unaspirated dental click sounds based on Zulu and *!Xσυ* consonants (Best et al., 1988; Best et al., 2003). The trials were split into six levels of difficulty, with two trials of clicks for difficulty one and five trials of clicks for each following difficulty. To increase task difficulty, duration between each click became greater over time: 2-12s in 2 second intervals. For the first block of trials, participants completed 27 trials made up of 2-12s delay (3 trials/delay), and on the second block completed 20 trials consisting of 6-12s delay (3 trials/delay). Both blocks took around 15 minutes to complete. Participants responded using one of two keys. The task was presented using Matlab R2017a.

Physical task. Participants wore a backpack weighted either 10% (light) and 20% (heavy) of their bodyweight for a total of 8 minutes (Proffitt et al., 2003). The participants were offered scales to determine their weight. In response to studies showing fatigue effects of physical effort tasks over time (Lopez-Gamundi & Wardle, 2018), light and heavy weights were alternated in 2 min intervals, resulting in four trials/participant to avoid rising physical effort costs.

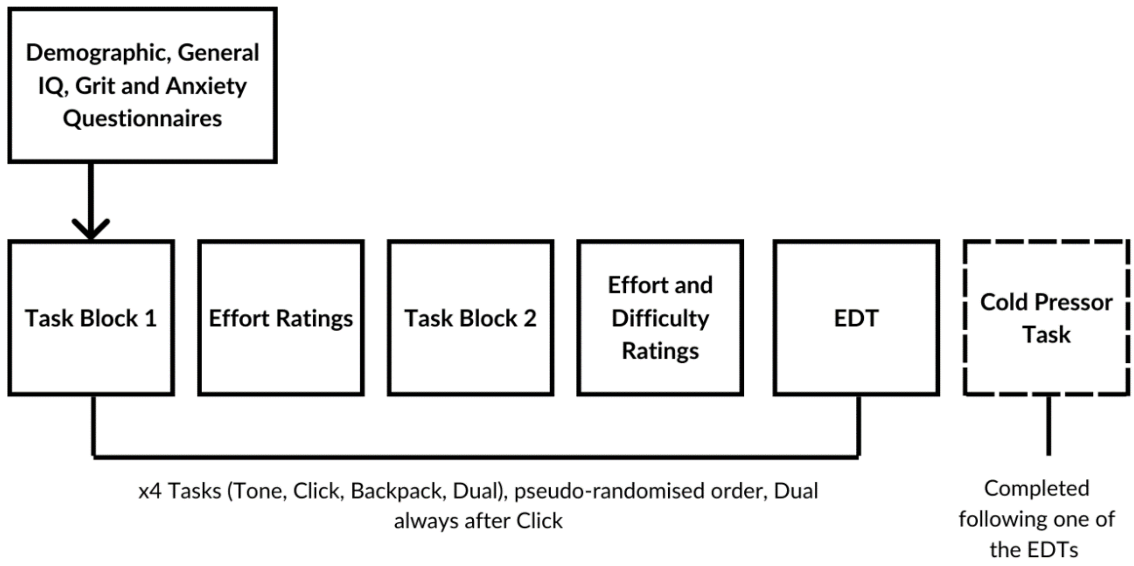
Dual task. Participants wore either the light or heavy backpack, counterbalanced between participants to not bias the Dual task, while performing two blocks of five trials of the Zulu click task. The Dual task took around 4 minutes to complete. The weight of the backpack matched the physical task. The difficulty of the two blocks were determined by the participants previous Zulu click task performance. For the two auditory tasks and the dual task, performance was calculated as the percentage correct of all trials.

Procedure

Participants were informed that the duration of the experiment would remain the same regardless of their performance and choices. Firstly, they filled out a demographic questionnaire, followed by a general Intelligence test and the psychometric questionnaires. The four tasks as outlined below, were performed in a pseudo-randomized order, except for the Dual task, which was always performed at any point after the Zulu click task. This meant that the difficulty of the Dual task could be calibrated based on the prior Zulu click task trials. Participants were asked to exert maximal effort while completing the tasks. Each of the single effort tasks were split into two blocks of trials, separated by subjective ratings of effort taken following each block. Ratings for difficulty were taken once after both blocks had been completed. Following this, the experimenter verbally presented the participant with the Effort Discounting Task to determine their SV of effort. The Cold Pressor Task was completed after two or three tasks. The experimental procedure was run as a socially distanced study; including the experimenter and participant wearing facemasks and sanitizing hands regularly, in line with university Covid-19 protocol. It lasted approximately 1.5hr (see Figure 5 below for full procedure).

Figure 5

Procedure of Questionnaires, Effort Tasks, Ratings, EDT and Cold Pressor for Study 1.



Analysis

Shapiro-Wilk Tests were used to assess normality for the overall perceived effort and difficulty ratings. The tests showed that only the perceived effort scores for Backpack (W = .98, p = .21), and the perceived difficulty of the Tonal task (W = .98, p = .27), were normally distributed. Based on the outcome of these tests, non-parametric Wilcoxon Signed-Rank Tests were used to compare the ratings of effort half-way and at the end of each task, as an indicator of fatigue. Wilcoxon Tests were also conducted to test differences in difficulty ratings between the hard versions of the tasks. We ran Spearman's Rho correlations to assess the relationship between SVs. This was complemented with a scatterplot matrix of the relationship between, and distribution of, SVs, and Bayesian Pearson correlations between SVs.

To address the question as to whether SVs of different tasks stem from shared or dissociated sources, we first conducted a Principal component analysis (PCA) and made Bayesian model comparisons. The PCA seeks to reduce the number of features and represent the data as linear combinations small number of eigenvectors, while preserving the variance (Jolliffe & Cadima, 2016). Secondly, we conduct a K-means cluster analysis on standardized data which seeks to reduce the number of data-points, to centre them by their expectations/means to represent linear combinations of clusters (Hartigan & Wong, 1979). Finally, as the SVs for all tasks were non-normal (Click, $W = .79$, $p < .001$; Tonal, $W = .78$, $p < .001$; Backpack, $W = .69$, $p < .001$; Dual, $W = .84$, $p < .001$), we ran a Friedmans Test to assess within-subject differences between effort scores for each task. We also conducted post hoc analysis using Wilcoxon Tests and interpreted a Bonferroni-corrected $p = .008$, to account for multiple comparisons.

To test if SVs of effort could predict general Intelligence, pain threshold, Grit, or Anxiety we ran six multiple regression analysis. To investigate the relationship between SVs and Intelligence further, a two-stage hierarchical multiple regression was run predicting Tonal Effort from Tonal task ability and Intelligence. To investigate the relationship between experience, ability, and effort further, a simple mediation analysis was performed. The outcome variable for the analysis was SV for the Tonal task. The predictor variable for the analysis was musical experience, and the mediator variable was performance on the Tonal task. The same mediation analysis was also performed with Zulu click task performance as the mediator variable to test specificity.

We accept significance at $p < .05$ level unless otherwise stated. Bayesian model comparison was done in Matlab (Bishop & Nasrabadi, 2006), and mediation analysis was conducted in SPSS using PROCESS (Hayes, 2017). To visually illustrate the relationships between willingness to exert effort across different tasks, we created a four-way Venn diagram in RStudio version 4.1.3 based on the overlap in SVs. Statistical analyses were run in SPSS (IBM, 2020) or Matlab R2016b (MathWorks, 2016).

Results

Perceived effort rated half-way and at the end of each single effort task, as an estimation of fatigue, significantly differed for the Tonal task, $Z = -2.89$, $p < .01$, with effort increasing with time, but not for the Zulu click, $Z = -1.5$, $p = .13$, or Backpack, $Z = -1.13$, $p = .26$, tasks. Average perceived effort as rated on a Likert scale, correlated significantly with SV for the Backpack task ($r(92) = -.22$, $p = .03$), but no other task ($p > .15$). Participants' ratings of task difficulty showed that the Backpack task was perceived as less difficult than Tonal ($Z = -5.65$, $p < .001$), and Zulu click ($Z = -5.30$, $p < .001$), whereas there was no significant difference between the Tonal and Zulu click tasks ($Z = -1.36$, $p = .17$). Perceived task difficulty correlated significantly with SV for the Zulu-click and Backpack tasks respectively ($r(92) = .3$, $p < .01$; $r(92) = .27$, $p < .01$), but not for the Tonal task ($p = .15$). Actual task performance correlated with SV for Tonal ($r(92) = .38$, $p < .001$) and Zulu click ($r(92) = .25$, $p = .02$), but not the Dual task ($r(87) = .20$, $p = .07$; Table 2).

Table 2

Descriptive Statistics Showing Averages and Standard Deviations for Each Measure in Study 1

	Average Block Completed	Perf Easy	Perf Hard	Perceived Effort 1	Perceived Effort 2	SV	M
Click	3.3 (=6 vs 8s)	73.8% (11.6)	73.1% (18.0)	5.7 (1.0)	5.5 (1.1)	1.54 (.55)	
Tone	5.4 (=5 vs 6 Tones)	50.3% (20.6)	45.0% (26.9)	5.7 (1.0)	5.8 (1.1)	1.60 (.51)	
Backpack	NA	NA	NA	4.2 (1.4)	4.2 (1.5)	1.71 (.46)	
Dual	3.3 (=6 vs 8s)	80.9% (20.0)	75.0% (21.1)	NA	NA	1.49 (.54)	
General Intelligence (1-12)							6.2 (2.7)
Grit (1-5)							3.2 (.6)

Anxiety (20-80)	35.8 (8.9)
Pain Tolerance (≤240)	123.7 (98.2)
Physical Activity (Hours per week)	4.4 (3.3)
Musical Experience (Years x Hours per week)	24.7 (81.9)
Backpack Weight (kg, Light)	6.8 (1.6)
Backpack Weight (kg, Heavy)	13.5 (3.1)
Click vs Backpack Perceived Difficulty (1-7, Hard vs Hard)	2.8 (2.0)
Tonal vs Click Perceived Difficulty (1-7, Hard vs Hard)	4.3 (2.0)
Tonal vs Backpack Perceived Difficulty (1-7, Hard vs Hard)	2.6 (2.0)

Note. Perf = performance, SV = Subjective Value.

Common or dissociated sources of Effort Discounting Task Subjective Values

Effort Discounting Task SVs correlated significantly positively with one another, with r values between 0.24-0.63 (Table 3). The scatter plot matrix (Figure 6) shows the co-relationships between the SVs. These findings are supported by a Bayesian zero-order Pearson correlation analysis using JZS method to estimate the Bayes factor. We find strong support for the alternative hypothesis for the correlations Tonal-Zulu click (*r* = .50 [.33, .64], *BF* = <.001), Tonal-Backpack (*r* = .27 [.08, .45], *BF* = .36), Tonal-Dual (*r* = .47 [.30, .62], *BF* < .001), Click-Dual (*r* = .47 [.30, .61], *BF* < .001) and Backpack-Dual (*r* = .36 [.17, .51], *BF* = .03). We find moderate evidence in support of the null (no correlation between SVs) between the Zulu click and Backpack tasks (*r* = .11 [-.10, .30], *BF* = 7).

Table 3

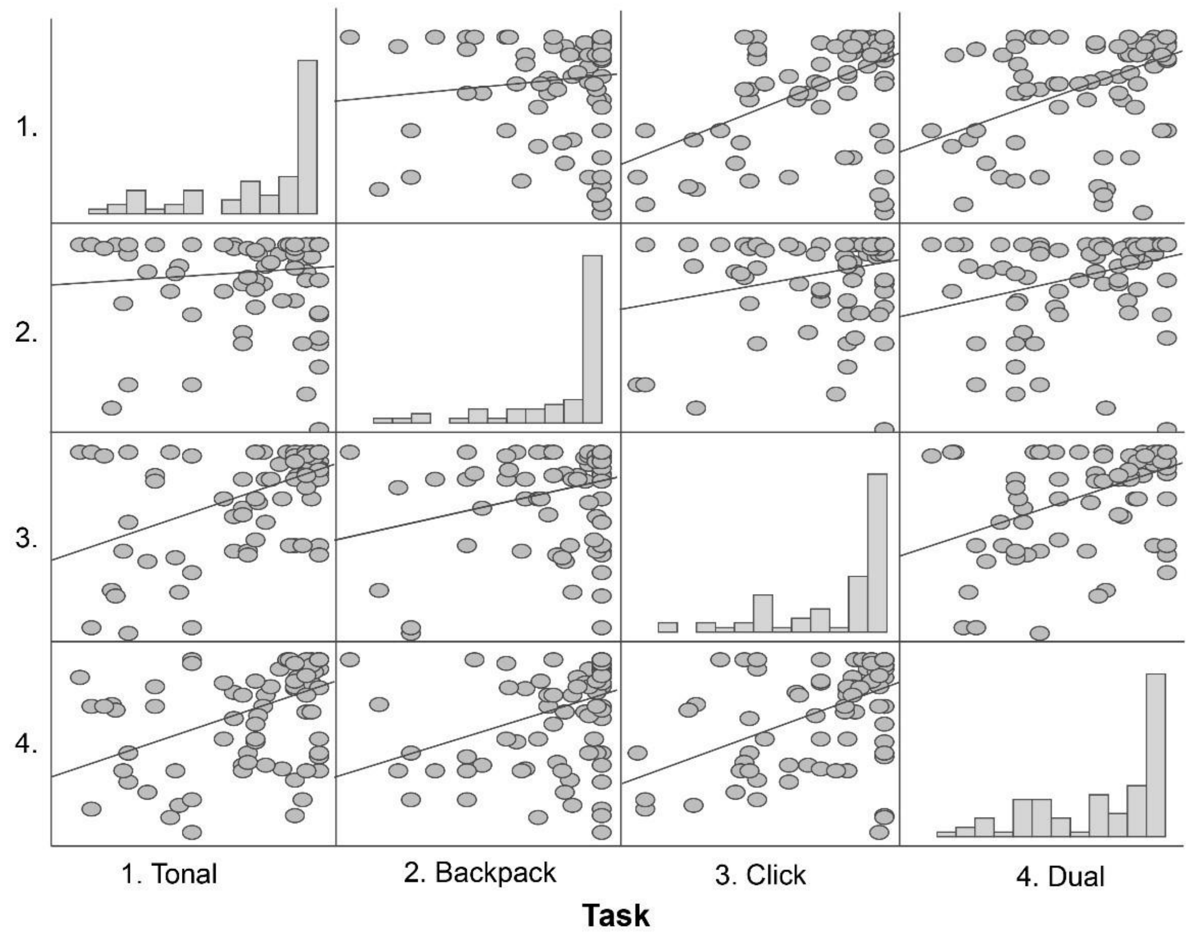
Correlation Matrix of Outcome Measures in Study 1

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Tonal SV	1	**.5****	**.32****	**.48****	**.32****	.12	.11	.08	.06	**.27****	-.20	.11	.05
2.Click SV		1	**.24***	**.63****	.14	**.22***	**.25***	.17	.16	.17	-.13	-.02	.11
3.Backpack SV			1	**.52****	.15	.15	.17	-.10	.03	**.23***	**-.27***	-.08	.09
4.Dual SV				1	**.30****	.09	.17	.10	.11	**.25***	**-.35****	.01	.16
5.Tonal Perf					1	**.42****	.16	**.41****	.08	**.89****	-.01	-.01	**.21***
6.Click Perf						1	.16	**.47****	.01	**.73****	.03	-.03	**.23***
7.Dual Perf							1	.15	-.11	**.23***	-.14	-.03	-.11
8.Music Exp								1	-.01	**.51****	-.04	-.05	.06
9.Phy Exp									1	.04	.07	-.16	.02
10.Raven										1	.01	-.01	**.22***
11.Grit											1	**-.21***	.05
12.S-STAI												1	.05
13.Pain (s)													1

Note. * p < .05. **p < .01 (two-tailed). SV = Subjective Value. Perf = performance. Exp = experience.

Figure 6

Correlations Between, and Distributions of, Subjective Values of Effort for Each Task as Measured with the Effort Discounting Task in Study 1



The PCA analysis of SVs of the four tasks showed that a PCA model with a single factor is the best explanation of the data. This had a Bayes Factor (Minka, 2001) of 3.2 greater than a model with 2 factors and 35.2 greater than a model with 3 factors. The factor matrix showed that the single source is weighted by the vector [.37 (Zulu click), .17 (Backpack), .33 (Tonal), .36 (Dual)] and explained 53% of the variance (Table 4a). This means that the Zulu click task, Tonal task and Dual task had similar, and the strongest, association to this factor. There was a close correspondence between the model covariance (Table 4b), and the empirical covariance (Table 4c). Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were satisfactory (KMO = .7, $p < .001$). The K-means cluster analysis allows us to suggest that two clusters are an appropriate estimation, as the three clusters analysis resulted in unstable iteration (>10 iterations), as well as non-significant differences between clusters for three of the four tasks. The $k = 2$ analysis, after five iterations, showed a significant difference between clusters for all four tasks: Tonal $F(90) = 45.5$, $p < .000$; Zulu click $F(90) = 98.0$, $p < .000$; Backpack $F(90) = 6.8$, $p < .01$; Dual $F(90) = 112.7$, $p < .000$. The sizes of the two clusters were 58 and 32 respectively, where cluster centres for each task represent positive values in cluster 1 (Tonal: .43 Zulu click: .56 Backpack: .20 Dual: .57) and negative values in cluster 2 (Tonal: -.76 Zulu click: -.94 Backpack: -.35 Dual: -.97; Figure 7). Thus, as shown in the PCA where variance was best explained with all four tasks as a single source, and in the cluster analysis where each cluster represented all tasks in the same direction, there is no clear distinction between tasks, nor domains. Investigating distribution of the SVs, we note that 28% were shared between all four tasks, and that the Dual task had the highest number of unique values (17%), which reflects its tendency of greater discounting. The relationship of SV distributions is illustrated in the Venn diagram (Figure 8), and average SVs for each task is tabled in Table 1. There was a statistically significant difference in SVs between tasks $\chi 2(3) = 24.03$, $p < .001$. Post hoc analysis showed a significant difference between Backpack and Dual SVs ($Z = -4.04$, $p < .001$), but not between SVs for Backpack and Tonal ($Z = -1.84$, $p = .065$), Backpack and Click ($Z = -2.62$, $p = .009$), Tonal and Click ($Z = -.29$, $p = .774$), Dual and Click ($Z = -1.13$, $p = .261$), or Dual and Tonal ($Z = -2.02$, $p = .043$).

Table 4a

Factor Matrix of the Resulting PCA of Subjective Values of Effort in Study 1

Variable	PCA Factor		
	1	2	3
Click task SV	0.365	0.000	0.000
Backpack task SV	0.165	0.000	0.000
Tonal task SV	0.333	0.000	0.000
Dual Task SV	0.367	0.000	0.000

Note. SV = Subjective value of Effort

Table 4b

Model Covariance Matrix of Study 1

Variable	1	2	3	4
1. Click task SV	0.133	0.060	0.122	0.133
2. Backpack task SV	0.060	0.027	0.055	0.060
3. Tonal task SV	0.122	0.055	0.111	0.121
4. Dual Task SV	0.133	0.060	0.121	0.132

Table 4c

Empirical Covariance Matrix of Study 1

Variable	1	2	3	4
1. Click task SV	0.308	0.027	0.142	0.141
2. Backpack task SV	0.027	0.209	0.063	0.088
3. Tonal task SV	0.142	0.063	0.261	0.13
4. Dual Task SV	0.141	0.088	0.13	0.290

Note. SV = Subjective value of Effort

Figure 7

Two Clusters with Cluster Centres Being in the Same Direction for All Four Tasks in Each Cluster in Study 1

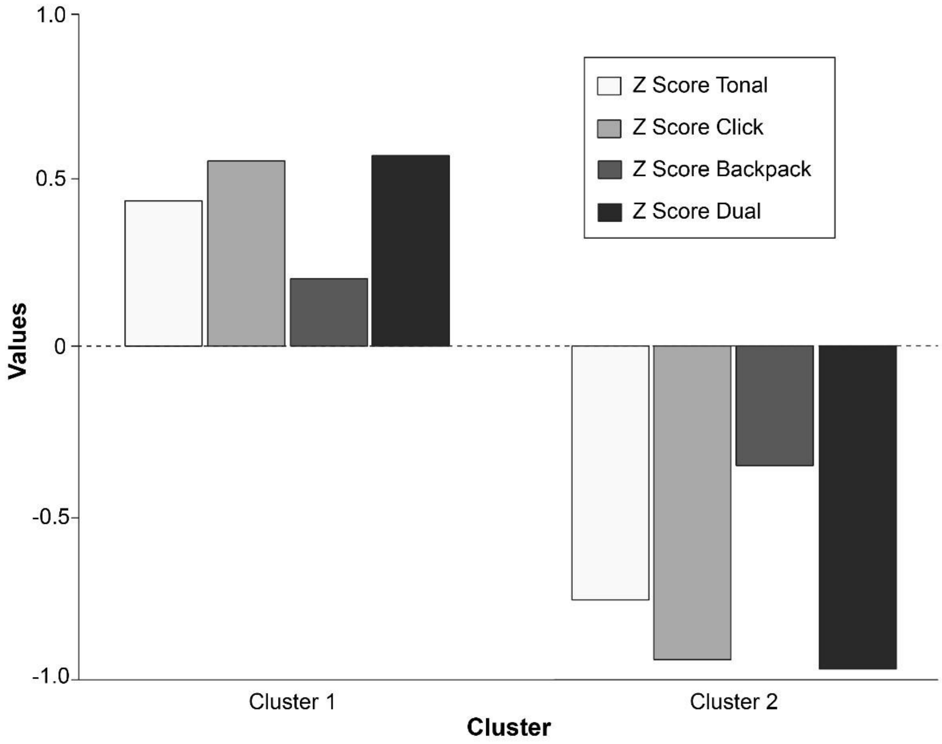
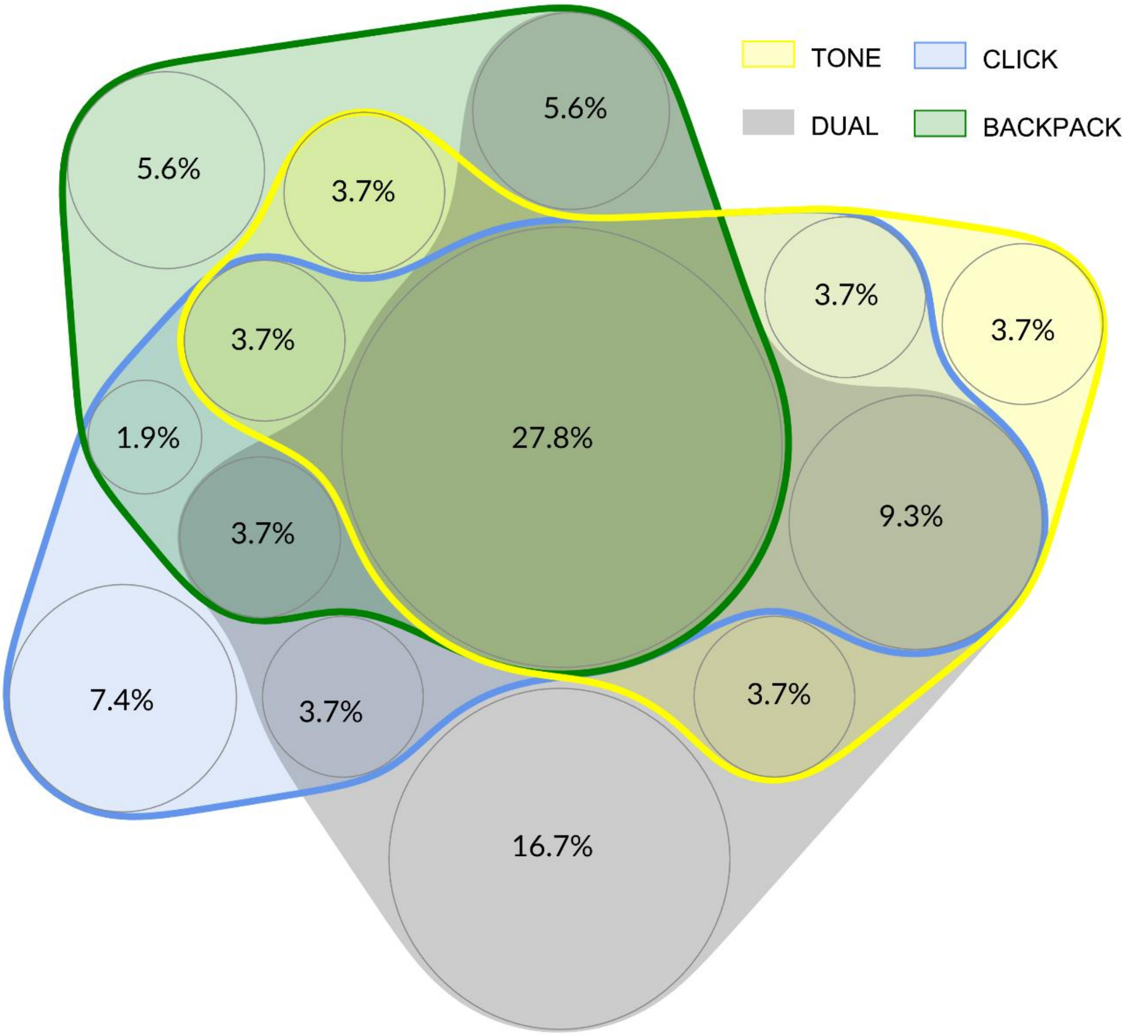


Figure 8

Four-Way Venn Diagram Showing the Overlap Between Subjective Values Across Effort Tasks in Study 1



Effort Discounting Task Subjective Value and trait-related measures

Multicollinearity between SVs of the four different tasks was not a concern for our regression analyses (Tonal, Tolerance = .66, *VIF* = 1.52, Zulu click, Tolerance = .67, *VIF* = 1.50, Backpack, Tolerance = .85, *VIF* = 1.18, Dual, Tolerance = .64, *VIF* = 1.56). SV scores could predict Intelligence scores ($F(4, 91) = 2.78$, $p = .03$), and the regression model indicated that they explain 7% of general Intelligence score variance. The regression models for Anxiety, pain, musical experience, and everyday physical activity did not yield any significant findings (*p* > .45). Grit was near significance (*p* = .06, Table 5).

Table 5

Results of the Six Multiple Regression Analyses Between Subjective Values and Constructs of Interest

Construct	*t*	*p*	β	*F*	*p*	adj. R^2
General Intelligence						
Overall Model				2.78	0.03	0.07
SV Tonal Task	1.09	0.28	0.71			
SV Click Task	0.56	0.58	0.33			
SV Backpack Task	1.86	0.07	1.2			
SV Dual Click Task	0.43	0.67	0.27			
Grit						
Overall Model				2.32	0.06	0.06
SV Tonal Task	-0.44	0.66	-0.06			
SV Click Task	0.8	0.43	0.1			
SV Backpack Task	-0.54	0.59	-0.07			
SV Dual Click Task	-2.29	0.03	-0.31			
Anxiety						
Overall Model				0.8	0.53	-0.01
SV Tonal Task	1.65	0.1	3.68			
SV Click Task	-1.18	0.24	-2.42			
SV Backpack Task	-0.44	0.66	-0.96			
SV Dual Click Task	-0.32	0.75	-0.68			
Pain (s)						
Overall Model				0.93	0.45	<-.01
SV Tonal Task	0.5	0.62	12.54			
SV Click Task	0.56	0.58	12.71			

SV Backpack Task	0.72	0.47	17.73			
SV Dual Click Task	0.48	0.63	11.63			
Pain (1-10)						
Overall Model				0.82	0.52	-0.01
SV Tonal Task	-1.57	0.12	-0.69			
SV Click Task	0.84	0.4	0.34			
SV Backpack Task	0.3	0.77	0.13			
SV Dual Click Task	-0.44	0.66	-0.19			
Musical Experience						
Overall Model				0.59	0.67	0.03
SV Tonal Task	0.48	0.63	0.06			
SV Click Task	0.7	0.49	0.09			
SV Backpack Task	-0.18	0.86	-0.02			
SV Dual Click Task	0.39	0.7	0.05			
Physical Activity						
Overall Model				0.87	0.48	0.04
SV Tonal Task	-0.6	0.55	-0.08			
SV Click Task	1.48	0.14	0.19			
SV Backpack Task	-0.44	0.66	-0.05			
SV Dual Click Task	0.49	0.63	0.06			

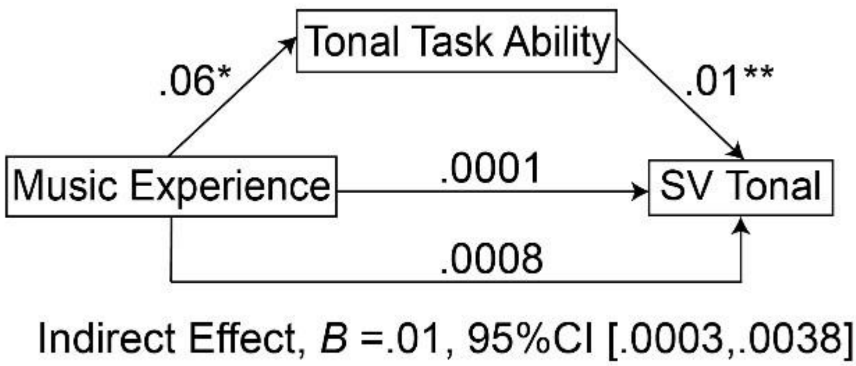
Note. SV = Subjective value of Effort

Investigating the ability hypothesis

The two-stage hierarchical multiple regression, further investigating the relationship between effort and ability, by using the SV of the Tonal task as the dependent variable, and performance (specific Tonal task ability) and intelligence scores (general ability) as the predictor variables, revealed that specific ability accounts for 14% of the SV variance (Step 1 $F(91) = 15.3$, $p < 0.001$, beta .38. Adj R^2 .14), and general ability added another 2% (Step 2 $F(90) = 9.8$, $p < 0.001$, beta .42, Adj R^2 .16), resulting in a 7:1 ratio between specific and general ability. None of the other variables; pain threshold, Grit, musical experience, everyday physical activity, nor Anxiety explained significantly additional variance in the model. We note that musical experience correlated significantly with performance on the Tonal task ($r(92) = .29$, $p < .01$), but not with performance on the Zulu click task ($r(92) = .20$, $p = .06$) (Table 2). The results from the mediation analysis showed that there is a significant indirect effect in that musical experience and Tonal performance predict SV of effort for the Tonal task; 95% CI is .0007, and CI95% = .0003 to .004, which excludes zero. Both path a (music experience on Tonal ability) ($B = .0639$, $p < .01$) and path b (Tonal ability on Tonal SV) ($B = .0105$, $p < .001$) were significant. There was no significant direct effect between musical experience and Tonal task SV ($B = .0006$, $p > .88$), nor was there a significant total effect ($B = .0008$, $p > .24$). Hence, Tonal task ability is considered as a mediator for musical experience on Tonal task SV (Figure 9). There were no significant effects when we tested if Zulu click task ability mediated the relationship between musical experience and SV for Tonal task ($p > .06$ for any path, the indirect effect: 95%CI is .0002 [-.0001, .0022]).

Figure 9

Mediation Analysis Showing Tonal Task Ability as a Mediator for Music Experience on Tonal Task Subjective Value of Effort in Study 1



Note. SV = Subjective Value, *p < .01, **p < .001

Discussion

We find that effort measures are consistent across tasks, as evident from the correlations between SVs, the PCA, the cluster analysis, and the Venn diagram. It should be noted however, that the correlation coefficients were higher between click and tone to backpack, and that the effort ratings of the physical task made the smallest contribution to the common component and clusters, and as such, was the item that deviated most from the others. Future studies should include several physical tasks within the same design to evaluate if physical tasks group more closely together.

When looking at what constitutes SV as measured with EDT, we find that competence and effort positively correlate for the click and tonal task. Interestingly, while the two correlated respectively, there are no correlations in these measures across the tasks. This suggests that effort may, in part, be related to abilities, and derive from more specific stimuli or task processes. This is supported by the findings from the mediation analysis showing that effort willingness for the music-related discrimination task is linked to musical experience via performance on the Tonal task, which was not the case for the non-music auditory task.

With regards to effort and general cognitive abilities, we find general IQ to relate to effort for the tonal and backpack task, as well as the four tasks together in the regression analyses. We found moderate support for a relationship between effort and grit, with significant correlations between grit and the backpack and dual tasks respectively. The tone task was also close to significance. Neither anxiety nor pain related to effort. This suggests that for effort calculations, the role of Anxiety and pain are task related. For pain specifically, the current study suggests that pain tolerance and effort willingness are dissociable when measured separately. Therefore, though participants will eventually choose pain over effort as shown by Vogel et al (2020), the current study shows that the level at which participants tolerate pain does not relate to choose between high and low effort tasks. This may be because our measure of pain entailed participants choosing ongoing pain or no pain (i.e., to remove their hand from the water), rather than directly between effort and pain. Such methodological differences could be removed in future designs, by offering participants choices between higher pain for more reward, and lesser pain for less reward, and relating this to effort discounting.

In summary, dividing effortful tasks into cognitive and physical domains appears to be of limited value, while specific task abilities may be of significance. In Study 2, we test these notions, and formally address whether effort can be categorized into cognitive and physical domains, or whether we should understand effort willingness based on other factors, such as the perceived task difficulty and experience.

Study 2a

In Study 2a, we collected effort ratings for various everyday activities online. These activities were chosen such that they were familiar to all respondents. This ensured that all could estimate the amount of effort each required. The tasks chosen were also varied within a domain. For example, we included cognitive activities that required emotion regulation, mathematics, navigation and task switching. Similarly, for the physical activities we chose not only exercise, but also activities involving planning and fine motor movements. Including such a variety allowed us to more rigorously test whether domain would drive effort perceptions, or whether the differences within a domain would matter to a greater degree.

We conducted a confirmatory factor analysis (CFA) to assess how well the latent variables cognitive and physical effort are estimated by eight observed effortful activities that we classify as either physical or cognitive. The CFA allows us to verify this factor structure and evaluate whether effort in different contexts is perceived to be distinct, given the literature suggesting there may be differences in effort evaluations for cognitive versus physical tasks.

We also correlated effort ratings to grit, to investigate whether perceived effort in daily life relates to participants passion and perseverance for long term goals (Duckworth et al., 2007). This is interesting given that high effort exertion is considered a central component of grit (Duckworth, 2016). However, as argued by Duckworth in 2016, it is the consistency of those individuals to continue to exert high effort over time that is a key marker of their grit, compared to their particularly high intensity of effort exerted. Additionally, she argues that gritty individuals do not necessarily put equal effort into all tasks, but rather that their efforts are aligned with a long-term goal. This does not however exclude the possibility that those with high grit demonstrate distinct patters of effort exertion in other areas compared to those with low grit. In addition to grit, we also correlate effort ratings with NFC (Cacioppo et al., 1984). We include NFC to test whether generally higher effort exerted in daily life is driven in part by greater NFC, or whether NFC is more specifically related to effort cognitive tasks.

Method

Sample

Data was collected from a convenience sample of 386 participants. All participants were students who signed up using a student research participation portal and were paid in credits. This was also the case for Studies 2b and 2c. 5 participants were excluded due to incomplete submission. The final dataset consisted of 381 participants (mean age: 22±7, 18-62yrs, 289 females). The study was approved by the ethical committee in the School of Psychology, University of East Anglia, EAN: 2021-0389-002413; ETH: 2122-0017.

Materials

Perceived Effort and Motivation. Perceived effort and motivation were measuring using a 5-point Likert scale. For effort, they were asked how much effort they typically exert when doing certain activities; '*I put in a lot of effort when…*' *(Strongly Agree* to *Strongly Disagree*). For motivation, they were asked how motivated they typically were when doing the activity; *I feel motivated when I…'*. Participants had the option to respond, '*Not Applicable',* in which case they were scored as *'Neither Agree nor Disagree'.* The sampling included the following eight activities: Calculate expenditure/budgeting, Inhibit negative emotions, Switch between tasks, and Follow a GPS in an unfamiliar environment; these are referred to as 'cognitive'. Exercise, Clean, Grocery shop, and Undertake personal maintenance; these are referred to as 'physical'.

Grit. The same 12-item Grit Scale as in Study 1 of this thesis was used to measure grit (Duckworth et al., 2007). The grit scale demonstrated strong internal reliability, with a Cronbach alpha coefficient of .78.

Need for Cognition. NFC was measured using the 18-item Need for Cognition Scale (Cacioppo et al., 1984). The NFC Scale evaluates the respondent's intrinsic motivation to engage in and enjoy effortful cognitive activities. Participants responded to statements such as 'I prefer complex to simple problems' on a Likert scale from 1-5, with higher total scores indicating greater NFC. Six of the items were reverse scored. The NFC scale demonstrated strong internal reliability, with a Cronbach alpha coefficient of .87.

Procedure

Data was collected via Qualtrics Survey Software (Qualtrics, LLC, Provo, Utah). The participants were asked about their age and gender. They were also asked what effort means to them from a pre-specified list: engagement, paying attention, being motivated, struggling, thinking a lot, getting tired, expending a resource, or exerting a force. This was followed by the 8 everyday activities where participants were asked to rate their effort and motivation. The activities were presented in a pseudorandomized order between participants. In addition, we asked participants to also complete the Grit and NFC Scales.

Analysis

A CFA two-factor model with eight observed variables (items), four for each factor, was configured in RStudio. Standardized and unstandardized estimates, tests for normality, and outliers, were computed. Our skewness and kurtosis values were all within acceptable limits of ±3. We compare the model output to conventional model fit indices: $p < .05$ for model Chi-square, root mean square error of approximation (RMSEA) < .05, comparative fit index (CFI) ≥ .95 and Tucker-Lewis index (TLI) ≥ .95 (MacCallum et al., 1996; West et al., 2012). Standardized factor loadings (std.all) were used to assess the strength and direction of the relationships between the latent variables and their respective observed variables. These loadings, scaled to fix the latent variable's variance at 1, allow for a direct comparison of loadings across different latent variables. We also correlated the average effort and motivation rating across all participants for each activity, and Grit and NFC scores, using Pearson correlations in SPSS.

Results

No single definition of effort stood out to the participants. Instead, they defined effort to imply engagement (*n* = 108), a force (*n* = 93), motivation (*n* = 65), a resource (*n* = 58), with similar preference, with a slight emphasis on engagement. Others defined it as attention (n = 12), struggling (*n* = 14), thinking a lot (*n* = 21) and getting tired (*n* = 10).

The CFA resulted in marginal fit, with some measures satisfying typically acceptable cut-offs (X^2 = 73.94 (19), $p < .001$, RMSEA = .09 (90% confidence interval = .07, .11), CFI = .82, TLI = .73) (Figure 10). All unstandardized factor loadings for items onto latent variables were significant ($p < .01$) and moderate to large (ßs > .30), except for exercise, which was not significant ($p = .28$), suggesting it to not be a good indicator of the latent construct. Our two latent variables significantly positively covary (Covariance estimate = .20, SE = .04, $p < .001$). Inspection of the standardized residual matrices of the observed samples were also within acceptable limits of ±3 (Byrne, 2001), except for between exercising and cleaning (5.01) and task switching and grocery shopping (3.63). The variance accounted for by the latent variables ranged between 66-99% ($p < .001$) for all the items, including exercise. To find exercise to not significantly load onto the latent variable while being a significant r-squared indicates that collectively, the latent variable explains a meaningful proportion of exercises variance. The covariance matrix showed no indication for stronger relationships between cognitive and physical tasks, respectively (Table 6).

Figure 10

Confirmatory Factor Analysis of Cognitive-Physical Model of Effort (N = 381) in Study 2a

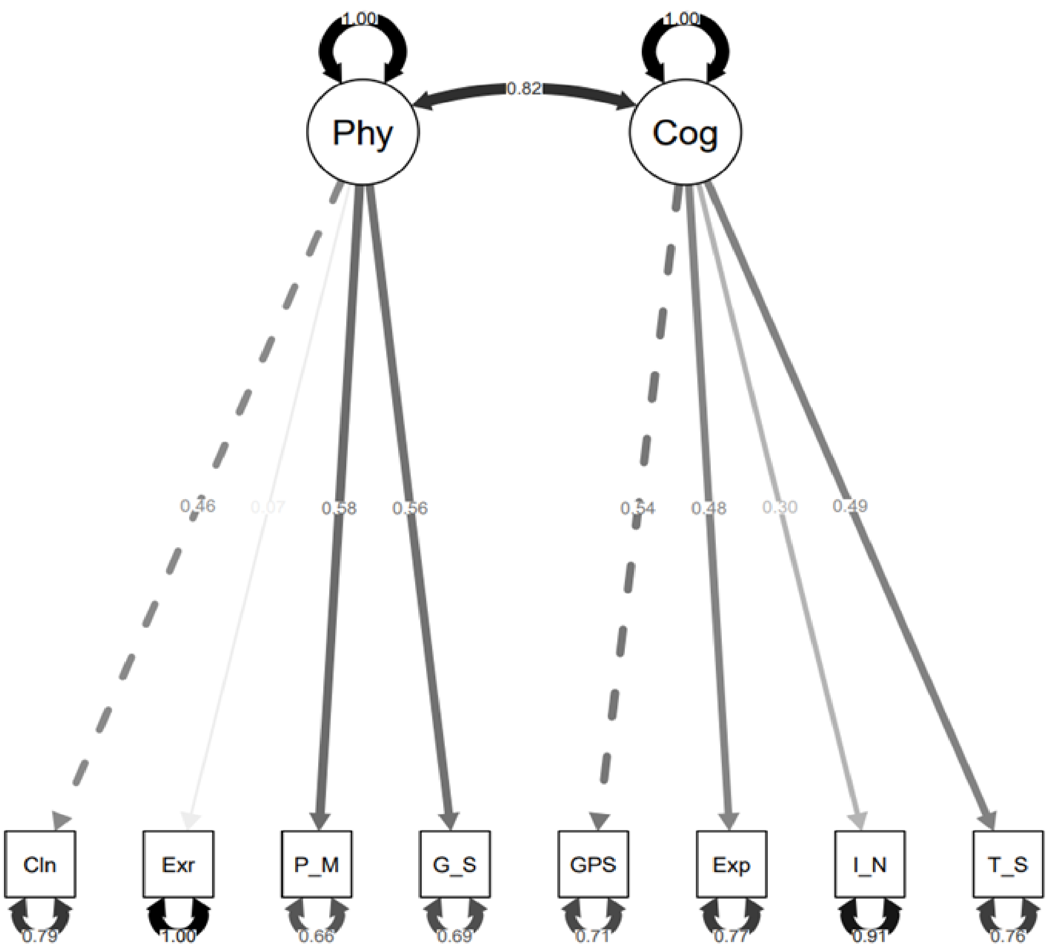


Table 6

Covariance of Effort for 8 Activities in Study 2a

Items	1	2	3	4	5	6	7	8
1. Exercise	0.820							
2. Clean	0.208	0.834						
3. Budget	-0.017	0.209	1.095					
4. Personal Maintenance	0.024	0.285	0.243	1.204				
5. Inhibit Negative Emotions	0.098	0.135	0.213	0.095	1.076			
6. Task Switch	-0.031	0.131	0.209	0.214	0.279	1.097		
7. Grocery Shop	0.045	0.211	0.217	0.429	0.082	0.415	1.295	
8. Follow GPS Unfamiliar	-0.028	0.238	0.344	0.341	0.089	0.277	0.300	1.234

The investigation into how Grit scores relate to effort ratings revealed that Grit correlated significantly with the eight-items effort ratings ($r(380) = .12$, $p = .02$). Grit also correlated significantly with the physical activities ($r(380) = .15$, $p < .01$), but not the cognitive activities ($r(380) = .06$, $p = .25$). NFC scores significantly positively correlated with the eight-items effort ratings ($r(380) = .12$, $p = .02$). It correlated significantly with the cognitive activities ($r(380) = .12$, $p = .02$), but not with physical activities ($r(380) = .08$, $p = .15$). Motivation ratings for each of the eight items significantly positively correlated with effort ratings, Personal maintenance $r(378) = .36$, $p < 0.001$, Follow GPS unfamiliar r(347) = .27, $p < 0.001$, Grocery shopping $r(374)= .30$, $p < 0.001$, Budgeting r(369) = .16, $p < .01$, Inhibit negative emotions $r(373) = .22$, $p < 0.001$, Task switching r(373) = .19, $p < 0.01$, Exercise r(375) = .16, $p < 0.01$, Cleaning $r(380) = .37$, $p < 0.001$).

Discussion

The first hypothesis-driven factor analysis reveals a marginal fit for a two-factor cognitive-physical model. However, the item Exercise does not turn out to be a good indicator of physical effort, contrary to what would be expected conceptually. This finding suggests that how people perceive and categorize required effort may not be as simple as to depend on whether a task is physical, or cognitive, to its nature. When correlating motivation to effort, the two concepts relate with R values spanning from 0.2 to 0.5. This suggests that experience and ability are central to how an individual perceives and categorizes effort. For future research, we note that, according to participants' reports, effort is an unspecific term which has different meaning to different people. It is viewed mainly as either engagement, a force, motivation, or a resource.

Study 2b – Part One

In Study 2b (Part One), we seek to replicate Study 2a with a novel sample. Therefore, we test whether weak model fit is once again found between participants perceived effort ratings when the eight activities are divided according to cognitive and physical, and whether effort and motivation ratings again positively correlate. The data for this sample derived from a subset of data from Study 2b– Part

Two, in which data was collected and analysed for a greater number of activities. Only data relating to the same eight activities as Study 2a is used in the analyses of this study.

Method

Sample

Data was collected from a convenience sample of 386 participants. 38 participants were excluded due to incomplete submission. The final dataset consisted of 348 participants (mean age: 23±9, 18-74yrs, 282 females). The study was approved by the ethical committee in the School of Psychology, University of East Anglia, EAN: 2021-0389-002413; ETH: 2122-0017.

Procedure

Data was collected using Qualtrics Survey Software (Qualtrics, LLC, Provo, Utah). The participants were asked about their age and gender. They were also asked what effort means to them, from the same pre-specified list as Study 2a. This was followed by the 8 everyday activities where participants were asked to rate on the same 5-point Likert scales as used in study 2a how much effort they typically exert when doing the activity and how motivated they typically are when doing the activity. Again, they could response '*Not Applicable',* in which case they were scored as *'Neither Agree nor Disagree'.* The sampling included the same eight activities from Study 2a. Participants were also asked to rate their effort for an additional 24 activities, though that data is not included in the present study and is analysed in Study 2b– Part Two of this thesis.

Analysis

A CFA two-factor model with eight observed variables (items), four for each factor, was set up. Again, skewness and kurtosis values were all within acceptable limits of ±3. We compare the model output to same fit indices as in Study 2a. We again correlated effort and motivation ratings, using Pearson correlations.

Results

Again, no single definition of effort stood out to the participants. They defined effort to imply engagement (*n* = 84), a force (*n* = 83), a resource (*n* = 65), and motivation (n = 60), with similar preference, with a slight emphasis on engagement. Others defined it as getting tired (*n* = 6), attention (*n* = 13), struggling (*n* = 13), and thinking a lot (*n* = 24).

The CFA resulted in good fit, with most measures satisfying typically acceptable cut-offs (X^2 = 27.16 (19), $p < .10$, RMSEA = .04 (90% confidence interval = .00, .06), CFI = .96, TLI = .93) (Figure 11). All unstandardized factor loadings for items onto latent variables were significant ($p < .02$, ßs > .20), except for exercise, which was not significant ($p = .33$). Our two latent variables significantly positively covary (Covariance estimate = .07, SE = .03, $p < .01$). Inspection of the standardized residual matrices of the observed samples were also within acceptable limits of ±3 (Byrne, 2001). The variance accounted for by the latent variables ranged between 61-99% ($p < .001$) for all the items. The covariance matrix however showed no indication for stronger relationships between cognitive and physical tasks, respectively (Table 7).

Figure 11

Confirmatory Factor Analysis of Cognitive-Physical Model of Effort (N = 348) in Study 2b Part One

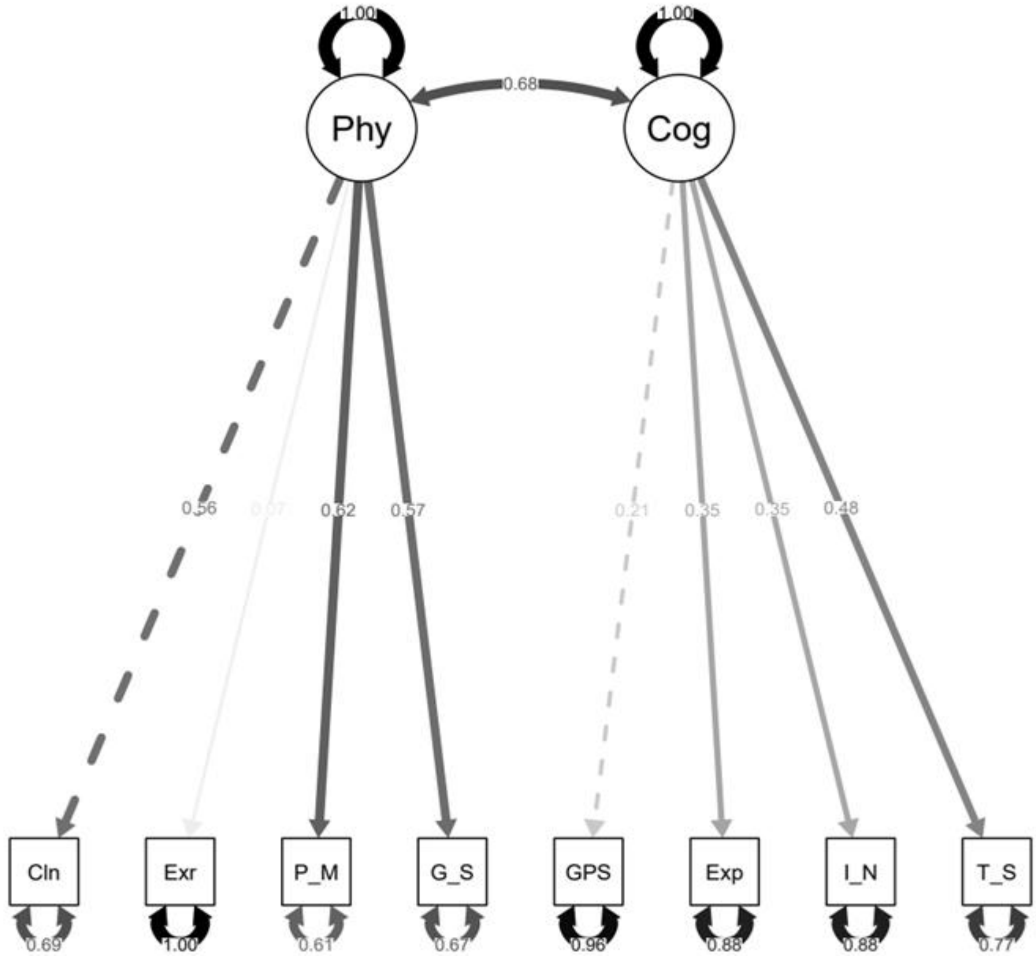


Table 7

Covariance of Effort for 8 Activities in Study 2b Part One

Items	1	2	3	4	5	6	7	8
1. Exercise	1.008							
2. Clean	0.024	0.802						
3. Budget	-0.024	0.139	1.014					
4. Personal Maintenance	-0.006	0.312	0.111	0.864				
5. Inhibit Negative Emotions	0.019	0.160	0.052	0.117	1.227			
6. Task Switch	-0.009	0.162	0.153	0.138	0.247	0.905		
7. Grocery Shop	0.111	0.247	0.216	0.339	0.153	0.188	0.992	
8. Follow GPS Unfamiliar	0.105	0.068	0.153	0.093	0.026	0.057	0.089	0.965

Motivation ratings significantly positively correlated with effort ratings for each of the eight activities (Personal maintenance $r(337) = .24$, $p < 0.001$, Follow GPS unfamiliar r(224) = .18, $p < 0.01$, Grocery shopping $r(331)= .21$, $p < 0.001$, Budgeting r(311) = .24, $p < 0.001$, Inhibit negative emotions $r(271) = .17$, $p < 0.01$, Task switching r(317) = .28, $p < 0.001$, Exercise r(320) = .17, $p < 0.01$, Cleaning $r(328) = .23$, $p < 0.001$).

Discussion

Unlike Study 2a, we find that the data provided a good fit for the model with cognitive and physical effort as separate latent variables, with these variables explaining large amounts of variation in effort ratings. To find that the overall model is supported, but that covariances do not align with whether a task is cognitive or physical, suggests that domain explains our data better than how individual task relate within a domain. Again, motivation was found to moderately correlate with effort, with R values spanning .17 to .28.

Study 2c

Given the previous inconstancies in how well domain explains effort, in Study 2c we ask participants to rate effort for a new set of ten tasks, five cognitive and five physical. In addition, we ask participants to categorize the tasks into being either cognitive or physical in nature, rate how fatiguing each task is, and complete the Need for Cognition Scale.

Method

Sample

Data was collected from a convenience sample of 48 participants (mean age: 34±12, 21-63yrs, 31 females). The study was approved by the ethical committee in the School of Psychology, University of East Anglia, EAN: ETH2223-2549.

Procedure

Data was again collected via Qualtrics Survey Software (Qualtrics, LLC, Provo, Utah). The participants were asked about their age and gender. They were then asked to rate the new set of ten activities on a 5-point Likert scale as to how much effort they typically exert when doing the activity; '*I put in a lot of effort when…*' *(Strongly Agree* to *Strongly Disagree*). Five of the activities were cognitive (Mental arithmetic, Reading a novel, Replying to work emails, Playing chess, and Writing an essay) and five were physical (Lifting a box, Dancing, Climbing stairs, Swimming for 30 minutes, and Hiking). To validate these categorisations, participants were asked to respond using a 5-point Likert scale the extent to which they considered each activity to be requiring cognitive or physical effort. They also had the option to respond, '*Both Cognitive and Physical'* or '*Neither Cognitive nor Physical'*. We also asked them to respond the extent to which they feel that the activities were fatiguing, using the same scale as the effort ratings. The activities were presented in a pseudorandomized order between participants. In addition, we asked participants to also complete the 18-item Need for Cognition Scale as used in Study 2a (Cacioppo et al., 1984). Again, the scale showed strong internal reliability, with Cronbach alpha coefficients of .86.

Analysis

A CFA two-factor model with ten observed variables (items), five for each factor, was set up in RStudio. Again, skewness and kurtosis values were all within acceptable limits of ±3, except for writing an essay, which had a kurtosis of 5.04. We include this item despite its leptokurtic distribution, as we can see that the distribution was caused by 44 of 48 of our responses being 4 or 5 on the five-point scale. We compare the model output to same fit indices as in Study 2a and 2b. We correlated effort ratings with NFC scores as well as ratings of fatigue, using Pearson correlations.

Results

As expected, participants rated mental arithmetic, reading a novel, responding to work emails, playing chess, and writing an essay as cognitive activities, and lifting a box, dancing, climbing stairs, Swimming for 30 mins, and hiking as physical activities (Table 8).

Table 8

Cognitive or Physical Activity Ratings for Study 2c

Activity	Cognitive	Physical	Both	Neither
Lifting box	0	41	3	2
Mental arithmetic*	44	0	0	2
Dancing	1	23	17	5
Reading novel*	43	0	1	2
Climbing stairs	1	38	4	3
Work emails*	39	0	4	3
Swim 30 mins	1	34	9	2
Chess*	40	0	3	3
Writing an essay*	44	0	1	1
Hiking	0	35	8	3

Note. *Categorised as cognitive. 2 participants did not rate the activities.

The CFA of SVs for each activity resulted in weak fit, with most measures satisfying typically acceptable cut-offs (X^2= 51.75 (34), *p* = .03, RMSEA = .10 (90% confidence interval = .04, .16), CFI = .85, TLI = .80). All unstandardized factor loadings for items onto latent variables were significant (*p* < .05) and moderate to large (ßs > .41), except for chess, which was not significant (p = .62). Our two latent variables significantly positively covary (Covariance estimate = .26, SE = .13, p = .04). Inspection of the standardized residual matrices of the observed samples were also within acceptable limits of ±3 (Byrne, 2001). The variance accounted for by the latent variables ranged between 23-99% (p < .001) for all the items except replying to work emails, which was non-significant. This suggests that effort for this activity does not fit with the cognitive latent variable as closely as mental arithmetic, reading, chess, and writing an essay. We are however cautious about the interpretability and generalizability of your results given the smaller sample size. Again, the covariance matrix showed no indication for stronger relationships between cognitive and physical tasks, respectively (Table 9).

Table 9

Covariance of Effort for 10 Activities in Study 2c

Items	1	2	3	4	5	6	7	8	9	10
1. Lifting Box	1.202									
2. Mental Arithmetic	0.284	1.393								
3. Dancing	0.445	0.24	1.34							
4. Reading	0.162	0.367	0.309	1.361						
5. Climbing Stairs	0.74	0.285	0.454	0.322	1.383					
6. Work Emails	0.563	0.603	0.423	0.566	0.421	1.329				
7. Swimming	0.508	0.276	0.356	-0.07	0.551	0.295	1.031			
8. Chess	-0.274	0.082	0.346	0.178	-0.311	-0.168	-0.258	1.133		
9. Essay	-0.111	0.373	0.148	0.448	-0.113	0.379	0.054	0.303	0.892	
10. Hiking	0.606	0.071	0.636	0.353	0.612	0.414	0.422	-0.04	-0.09	0.989

NFC scores significantly negatively correlated with the cognitive activities ($r(42)$ = -.31, p = .05), but not with physical activities ($r(42)$ = .13, p = .41). Fatigue ratings significantly positively correlated with effort ratings for five of the ten activities (mental arithmetic $r(45)$ = .35, p = .02, dancing $r(45)$ = .30, p

= .05, reading a novel $r(45) = .30$, $p = .05$, climbing stairs $r(45) = .48$, $p < .001$, and hiking $r(45) = .38$, $p = .01$). Correlations for all other activities were non-significant ($p > .06$).

Discussion

The third hypothesis-driven factor analysis reveals a weak fit for a two-factor cognitive-physical model. These finding suggests that how people perceive and categorize required effort may not be as simple as to depend on whether a task is physical, or cognitive, to its nature. When correlating NFC to effort, again effort for cognitive tasks relates, but this time in a negative direction. Fatigue can be correlated with effort for both cognitive and physical activities.

General Discussion

Here, we have investigated two estimations of effort: The willingness to exert prospective effort in exchange for money, by using a titrating discounting task (Study 1), as well as retrospective estimations of effort put into various general activities rated by participants on a Likert scale (Study 2). These are two different ways of measuring effort; one is a relative measure of effort where the SV is sensitive to the reward amount and perceived task demand captured at one time point (Westbrook et al., 2015). The other measure represents opportunity costs to a lesser degree, since it is a retrospective, average-based effort estimation over time, of activities; many of which in Study 2a and 2b are mandatory and performed more or less daily. As such, they could be argued to represent, to a greater extent, a model-free (habitual) control of behaviour, whereby cost-benefit calculations are less explicit at any given time point (Westbrook et al., 2015).

Notably, in neither of these studies do we find support for the cognitive-physical divide. Instead, we find consistencies in effort estimations within individuals across tasks, as evident from the correlation and covariation matrices. This speaks to theories on embodied cognition proposing that cognition and bodily states are tightly linked, where cognition is in part shaped by the body, and vice versa (Wilson & Golonka, 2013). However, to propose that everyone has an amodal, common effort system would be an oversimplification. Our data also points to the notion that differences in effort arise, in part, due to factors intrinsic to the interaction between the individual and the particular task. For example, in Study 1, we find a task specific indirect effect of musical experience and Tonal ability on Tonal effort. We also find, in Study 2, that neither effort for everyday tasks, nor for rarer, more effortful tasks that either primarily cognitive or physical, can be consistently understood in terms of domain. Thus, effort calculations appear to be an experience-based, plastic system, where the central core of effort estimation is pulled outwards in various directions as personal experience grows. Our findings resonate well with leading cost-benefit models of effort, proposing that effort calculation for a task is partly based on the individual's knowledge about their anticipated task performance (Shenhav et al., 2013). In fact, athletes with many years of experience in physical exercise put more effort into a physical task, and perform the task for longer, even when the task is adjusted to their individual ability, and they perceived the task to be just as demanding as non-athletes (Chong et al., 2018). These athletes also viewed cognitive effort differently, with lesser reward devaluation at low cognitive load. It is still unclear what drives these changes in effort calculations (Otto & Daw, 2019), but these studies suggest that experience and effort willingness are related. Novel studies have found that indeed, effort seems possible to train. Rewarding effort, instead of performance on a cognitive task, leads to an increased tendency to choose a harder version of an unrelated cognitive task (Clay et al., 2022). Our findings are also in line with Morris et al. (2020), who did not observe any difference between cognitive and physical tasks in how participants biased reward against rising costs, as well as the overarching idea from neuroimaging studies that an amodal evaluation network exists to integrate and process information for different types of tasks in the service of SV calculation (Chong et al., 2017; Schmidt et al., 2012).

In our investigation of everyday activities, we find that there are only moderate correlations between motivation and effort ratings. These findings help clarify the nature of the relationship between motivation and effort, which is largely lacking in the literature, and are in line with the notion that effort and motivation are in part separable constructs (Pessiglione et al., 2018). From our results, it seems that effort is not necessarily tied to overall motivation. We propose that this because effort is a function that assists in the computation of expected value within motivation. This slightly deviates from effort as a cost as may be interpreted from the original EVC model (Shenhav et al., 2013), but is in line with recent studies showing that effort seems to influence estimation of value beyond simply as a cost (Clay et al., 2022).

Some studies suggest that there is a genetic component to effort that contributes to the willingness to exert effort, and hence the individual gains experience (Mosing et al., 2014). Manzano and Ullén (2021) find close to a 1:5 ratio of general Intelligence and musical ability (SMDT) contributing to long-term piano practicing and achievement, both partly heritable (Deary et al., 2006; Ullén et al., 2014). In Study 1, we find that general Intelligence predicts small but significant increases in willingness to exert effort. We also find that general Intelligence and Tonal task ability predicts effort willingness with a 1:7 ratio. Lopez-Gamundi and Wardle (2018) also find a significant correlation between willingness to exert cognitive effort and working memory capacity. This is in line with our, and Culbreth et al.'s (2019), finding that NFC scores correlates with effort ratings, for cognitive activities in particular. Thus, the proposal that willingness to exert effort has a genetic basis is potentially fruitful.

Grit, which is a measure of several goal related aspects, including both effort and more affective components (Duckworth et al., 2007), predicted SV with near significance (p = .06) in Study 1. In Study 2a, we also find that Grit scores correlate with average effort rating, mostly driven by physical activities. In Study 1, perceived effort, as an estimation of fatigue, increased over time for one of the cognitive tasks, but for the other cognitive or physical tasks. In Study 2c, we find that fatigue significantly related to effort ratings for half of the activities, across a mixture of cognitive and physical activities. Neither the findings from grit nor fatigue provide support for effort domains.

When looking at how effort relates to performance, in Study 1, we find correlations between task performance and effort willingness ranging between non-significant to significant r = 0.4, which means that greater performance is not necessarily accompanied by greater effort willingness, when offers are adjusted to each individual’s capacity level. As highlighted by Westbrook and Braver (2015), there are plenty of situations in which effort and performance can be dissociated, for example, in data-limited tasks, such as reading visually degraded words, which can be difficult without necessarily being effortful. The distinction between effort and performance is also supported by Lopez-Gamundi and Wardle (2018), who found a weak relationship between performance and effort, across cognitive and physical tasks. We note that there was a tendency for the Backpack task in Study 1 to differ from the others in that participants perceived it to be the least difficult and were more willing to repeat harder condition for reward, and so we welcome further investigations to include more than one physical task.

When it comes to pain, it has been observed that inter-individual differences in 'pain catastrophizing scores' help determine to what degree cognitive effort is exerted to avoid pain (Vogel et al., 2020). Unlike the current study however, the authors did not measure participants' pain threshold. Our data suggests that sensitivity to pain is of lesser relevance in effort cost-benefit calculations of simple, shorter cognitive and physical lab-tasks. It should be noted that the results of Vogel et al. (2020) show asymmetry between cognitive effort and physical pain willingness in decision time, leaving the relationship between pain sensitivity and effort levels unclear. Anxiety scores did not matter for effort willingness in our study. As previously described, the Processing Efficiency Theory (Eysenck & Calvo, 1992) stipulates that anxiety plays a role particularly in high stake scenarios, which is supported by empirical studies (Berchio et al., 2019; Hardy, 1999; Hardy & Hutchinson, 2007). In these studies, participants typically take part in a high-stake trial without the possibility to choose an easier option. In our study, Anxiety scores were analysed in relation to the SV where participants were given the option to choose between an easier and a harder task, both adjusted to their capacity level. This may counter-balance the typical effect that anxious individuals tend to try harder the more that is at stake (Berchio et al., 2019). In addition, Charpentier et al. (2017) find anxiety to be related to the propensity to take risks, rather than error aversion. Thus, an effect may be visible in uncertain contexts, of which we had little.

In conclusion, while traditionally, there has been a temptation to treat effort as stemming from either a physical or a cognitive estimator, our results show no support for such a divide. Instead, it is likely that effort is simply a function of the brain that assists in the estimation of value, which naturally involves processing information that is both cognitive and physical by nature.

CHAPTER FOUR: COMPETENCE AND TASK FREQUENCY, BUT NOT AFFECT, MATTER FOR EFFORT

Chapter Introduction

In Chapter Three, we find weak support for effort dividing according to domain. We find that neither effort willingness in the lab nor self-reported effort in daily life divides according to domain. Instead, we find from the correlations, cluster analysis, and spread of SVs that effort appears to be largely domain general. The existence of an amodal effort function that can process both information relating to cognitive and physical tasks makes sense from an evolutionary perspective (Pinker, 2003), in terms of efficiency, compared to two separate systems. In this chapter, attention is shifted towards the other aspects that matter for effort-based decisions within a domain.

Classical theories stipulate that both competence and affect play important roles for motivation. For example, the Expectancy Value Theory (EVT; Vroom, 1964) distinguishes between Expectancy, which is largely driven by ability, and Value, which is largely driven by affective components such as enjoyment. Support for such perspectives come from research showing that competence and affect separately predict effort (Pinxten et al., 2014; Timo et al., 2016). When it comes to the effort literature specifically, competence is included as a key aspect of expected value calculation. Specifically, competence is theorised to direct impact SV through performance efficacy. Therefore, if an individual is able to achieve a desired outcome state, then they will discount the payoff associated with the control signal in question less and/or will perceive the costs to be lower (Shenhav et al., 2013). As highlighted by Grahek et al. (2020), it is plausible that affect may also influence estimations of each of these estimations. For example, the expected outcome of a behaviour may be influenced by their affective salience (Slovic, et al., 2007), which itself can be influenced by the person's current mood (Clore et al., 2001; Eldar et al., 2016; Isen et al., 1988). This also likely applies to the perceived difficulty of a task (Gendolla et al., 2001), as well as estimations of costs, e.g., effort (Cléry-Melin et al., 2011). However, the role of affect in value estimation is not explicitly addressed in the EVC.

Elsewhere in the literature, Malesza (2021) found that an individual's emotion regulation related to the extent of their delay discounting. Specifically, they found that negative affect was directly related to greater delay discounting. If emotions therefore influence the impact of delay on SV, it seems plausible that it would have a similar effect when it comes to effort too. Previous research on effort suggests that negative affect may signal that things are not going well (Carver, 2003). Foo et al (2009) expand upon this and shows that effort exertion in everyday life can be increased by both high positive and negative affect respectively. Both studies support the notion that effort-based decisions may be influenced by the respondent's affective state. Effort being influenced by affect may also explain why studies find COG-ED responses to positively correlate with NFC, whereby less effort discounting was associated with greater NFC (Mækelæ et al., 2023). Therefore, individuals who are less prone to discounting reward for effort are more likely to engage in and enjoy cognitively demanding tasks. It may be that the positive affect experienced by those with high NFC during cognitively demanding tasks may in-part explain their higher effort willingness, though this requires subsequent investigation.

Rather than manipulating mood by asking participants to watch a sad movie as done by previous effort research on depression (Westbrook et al., 2022), a novel approach employed in the current chapter is to manipulate the enjoyability of specific stimuli. Therefore, rather than assessing the impact of overall affect of participants (e.g., their sadness, boredom, anger), in Chapter Four the impact of the enjoyability of specific tasks on effort willingness is tested. Such a design tests whether the enjoyability of tasks also matters, or whether the enjoyability of tasks only matters for effort insofar as it manipulates mood. To this end, we ask participants to make effort-based decisions relating to two versions of the same task, one with enjoyable sound stimuli and one with neutral sound stimuli. This asks a more specific question than previous work, as rather than looking to manipulate mood, we instead manipulate the enjoyability of the task stimuli and assess resultant changes in effort-based decisions while controlling for order effects. We also follow this up by reanalysing the data relating to the 8 activities in Study 2b – Part One, as well as data for an additional 24 items collected from the same participants at the same time. This time, we use exploratory factor analysis to understand participant perceived effort and interpret the factors using task ratings from independent samples.

Effort also has clinical relevance. For example, studies show that effort measures in the lab can relate to several disorders such as depression (Treadway et al., 2012), schizophrenia (Gold et al., 2015), and ADHD (Volkow et al., 2011). Given the growth in remote testing of disorders (Kim & Xie, 2017), it is of relevance that we understand the suitability of effort measures for online administration. Currently, studies have adapted effort measures for online administration (Bustamente et al., 2023), but have not compared the same conditions in the lab and online. Therefore, an understanding of how effort can be tested remotely is needed. In response, as an additional exploratory aspect, we do just this, and compare online versus lab responses of effort between-subjects to assess initial trends for future analyses.

Abstract

The Expectancy Value Theory on motivation stipulates a dissociation between perceived competence and task enjoyment in how behaviour is directed. This is supported by findings from the education literature showing distinctions in the predictive capabilities of these two aspects on learning outcomes. While effort is typically conceptualised as an important aspect of motivation, leading models of effort are yet to account for the role of enjoyment. Given that effort willingness has been shown to have both educational and clinical relevance, better understanding the role of both competence and enjoyability is likely useful. Problematically, studies of effort tend to use a single task, or two different tasks, making it difficult to disentangle the contribution of the task and the individual. We firstly performed exploratory factor analyses of effort ratings of 32 everyday activities, from 386 online responses. The data for 24 of these items has not been analysed in this thesis thus far, though the data for 8 activities has been used in Study 2b – Part One. Effort was best understood in terms of perceived competence, as well as how often a task is undertaken, rather than how enjoyable a task is perceived to be. In a separate second study, we asked 106 participants to complete two versions of a sound discrimination task, where the sound stimuli were either music or language-related sounds. We then asked them to make effort-based decisions relating to each version, and make ratings of perceived competence, enjoyment, and engagement. We hypothesised that competence and affective components would have distinct effects on effort. As an additional manipulation, we also collected half of the data in the lab, and half online. We find the music-related task to be perceived as more enjoyable and engaging, but that this did not drive differences between the two versions in effort choices. We also do not find musical experience, or self-reported depression to matter, though we did find that actual competence for language-related version related to effort for both versions, but not for the music-related version. Additionally, when it comes to perceived competence, we find that the ratings for the music-related version predicted effort for the same version, but no other relationships were significant. Such findings suggest that competence, both perceived and actual, has differing impacts on effort than enjoyment. Depression and music experience had no influence on

effort willingness in typical healthy, non-music expert populations. When it comes to context, we find greater effort willingness from responses in the lab, despite no differences in enjoyment and engagement. This was largely replicated in an online replication. Taken together, such findings align with the motivation literature and suggest that focus should be placed on competence and experience, when predicting an individual's effort across tasks, and when designing interventions.

Introduction

Effort influences the time we spend and the intensity we commit to performing everyday tasks, from cleaning and cooking, to learning and working. This is because effort is thought to influence the 'cost' associated with a task, which in turn mediates the expected value to which we estimate it to have. According to the Expected Value of Control Theory (EVC; Shenhav et al., 2013), the allocation of cognitive control (i.e., goal-directed behaviour) is determined by whichever choice yields the greatest expected value. The outcome of this cost-benefit analysis is understood to be driven by an interaction between the individual and the characteristics of the target task before them (Shenhav et al., 2013, 2017; Walton & Bouret, 2019; Westbrook et al., 2020). For example, it has been shown that effort-based decisions are influenced by an individual's ability (Manzano & Ullen, 2021), anxiety (Berchio et al., 2019; Putwain & Symes, 2018), and level of fatigue (Iodice et al., 2017; Lopez-Gamundi & Wardle, 2018). Likewise, task relevant aspects such as task difficulty (Westbrook et al., 2013), task duration (Lopez-Gamundi & Wardle, 2018), and outcome reward (Schmidt et al., 2012; Klein-Flugge et al., 2015) impact effort-based choices. Data from a recent study using computational modelling also suggests that individual's estimations of their task competence may not be fixed, and instead may account for the task learnability and potential future competence gains (Masís et al., 2021), which nicely demonstrates the relevance of both individual and task-specific aspects in effort-based decision-making.

In a similar manner, the Expectancy Value Theory (EVT), first proposed in the 1960s (Vroom, 1964; Eccles, 2005) attempts to explain Motivation as a product of *Expectancy*, which is the probability that a wanted outcome is achieved based on and individual's belief about their ability to manage the task, and their effort willingness, and *Value*, which reflects how much the individual values the desired outcome, including the degree of enjoyment, personal importance, how well the task fits with current goals, as well as effort costs. Thus, effort is conceptualised as an important aspect of motivation, which is further supported by studies showing that lower effort willingness; the preference for completing a less demanding task for less reward compared to a more demanding task for more reward, is associated with depression (Berwian et al., 2020; Cléry-Melin et al., 2011; Cohen et al., 2001; Treadway et al., 2012), and lower overall global functioning in daily life (Westbrook et al., 2022). Conversely, grit, which reflects high effort willingness over time, is linked with many desirable outcomes, such as academic attainment (Disabato et al., 2019), greater health (Credé et al., 2017), and increased socio-economic status (De Ridder et al., 2012).

While researchers agree that effort plays an important role in motivation, few studies have investigated how they may differ and what aspects of the cost-benefit analysis specifically modulate effort willingness. The competence-enjoyment distinction postulated by EVT (Vroom, 1964) has rendered interest in educational research in studying the academic self-concept and achievement emotions (Arens et al., 2011; Pinxten et al., 2014; Timo et al., 2016). In a longitudinal study, with six years in between data sampling, Timo et al. (2016) found that perceived physical activity competence predicted their reported physical activity level at the second time point, while their reported enjoyment for physical activity did not. Likewise, Pinxten et al. (2014) longitudinally investigated differential effects of perceived competence and task enjoyment on mathematics achievement in primary school children. As expected, a confirmatory factor analysis model where enjoyment and competence beliefs were treated as separate factors, rather than one, explained maths achievement the best. Notably, they found that perceived competence significantly relates to maths effort, while enjoyment had none, or in one of their models 'a limited positive effect on subsequent exerted effort in math'. This finding outlines a dissociation between effort and motivation in that affective components may be less relevant for effort than the sense of competence. It is also in line with the argument made by Pessiglione et al. (2018), in their model on goal oriented motivational behaviour, that affective components may act as proxies for evaluating a given state, rather than guiding optimal behaviour. This argument is based on their findings that instrumental effects maps to incentives, whereas emotional arousal has a 'limited effect size' and dissociated neural processes (Pessiglione et al., 2018).

Despite evidence for a competence/affect divide in the motivation literature, the EVC does not specifically address the role of affect in value estimation. As highlighted recently by Grahek et al (2020), affect may plausibly impact estimations of outcomes (Slovic et al., 2007), the perceived difficulty of the task (Gendolla et al., 2001), and estimations of cost (Cléry-Melin et al., 2011). However, during current measures of effort, affect is not manipulated. Instead, it is aspects such as task load, likelihood of reward, and reward level that are changed (Ang et al., 2022; Bustamante et al., 2023; Chong et al., 2015; Treadway et al., 2009; Westbrook et al., 2013). On the role of affect for effort, a study by Foo et al (2009) showed that entrepreneur's valence in either direction (both positive and negative) influenced the self-reported effort they put into their business venture. Such a study suggests that affect may act as a signal to either put in more effort if things are going badly, or as a motivator if things are going well. However, when using a choice-behaviour measure of effort in the lab, Westbrook et al (2022) find no difference in effort between healthy subjects who either watched a sad or a neutral movie.

Rather than manipulating overall mood, one novel design employed in the current study is to instead manipulate the enjoyability of stimuli while keeping all other aspects of the task constant. This way, the impact of enjoyability can be assessed. If the enjoyability of stimuli is found to influence the SV of effort, there are valuable practical implications to be gained. For example, when designing learning material and interventions in educational and clinical settings, from understanding if 'how fun a task is' is of relevance to effort willingness, or if the individual's perceived competence plays a larger role, as suggested by a few, but well-designed studies (Pinxten et al., 2014; Pessiglione et al., 2018). In the current study we investigate this by firstly conducting an exploratory factor analysis on effort ratings of a number of everyday activities. We then map enjoyment and perceived competence ratings to better interpret these factors. Secondly, we build upon previous designs by comparing effort willingness within-subjects as well as within-task. We use an auditory sequence discrimination task where the stimuli used are either piano tones (Ullén et al., 2014) or non-western Zulu clicks (Best et al., 1988; Best et al., 2003). We know from previous observations that the piano tones are perceived as more enjoyable, whereas competence on the two versions of the same task should not differ. Effort willingness is measured using the effort discounting task procedure (Westbrook et al., 2013). In addition, we test if previous music experience, and the number of languages spoken, i.e. experience, matter for effort willingness, and collect depression scores (from the non-clinical population). The stimuli is selected to that participants with music experience are expected to perform better on the music-related task, but not necessarily for the foreign language task (McKay, 2021; Swaminathan & Schellenberg, 2017).

Since effort measures typically involve the exertion of physical effort (Lopez-Gamundi & Wardle, 2018; Treadway et al., 2009) or require the use of specialist equipment (Richter et al., 2008), it has traditionally been measured in the lab. However, when measuring effort on cognitive tasks, it is possible, when using the effort discounting task, to collect data online (Bustamente et al., 2023). This opens for the possibility to compare effort willingness for tasks conducted online and in-person. This is useful given the increasing popularity in educational online learning classes (Schwartz et al., 2020), and the growth of remote electronic health services (Kim & Xie, 2017). Despite this, only one study includes both in-person and online effort willingness to date (Embrey et al., 2023), though they did not include equivalent online and in-person conditions for direct comparisons. Thus, in Study 3 we collect data both online and from the lab to investigate the influence on effort willingness, enjoyment, and competence.

Study 2B – Part Two

Participants' ratings of perceived effort exertion on 32 everyday activities, such as cleaning, cooking, playing board games, and reading the news were classified into factors in an exploratory factor analysis. To assist in our interpretation of EFA factors, we map how each factor is related to ratings of perceived competence, how often an activity is exercised, enjoyment, and self-relevance.

Method

Sample

Data derived from the same sample as Study 2b Part One and was a convenience sample of 386 participants. Therefore, all participants were students who signed up using a student research participation portal and were paid in credits. 38 participants were excluded due to incomplete submission. The final dataset consisted of 348 participants (mean age: 22±9, 18-74yrs, 282 females) for the 32-item exploratory analysis. The study was approved by the ethical committee in the School of Psychology, University of East Anglia, ETH2122-0017.

In order to get ratings of competence (*'I feel competent when…'*) and self-relatedness (*'Indicate whether you find the activity to be mostly focused towards yourself, or focused towards the external world'*) on these activities, we collected data from independent groups of participants (*N*comp = 187, *N*self = 137). Gathering this additional data relating to the task difficulty and self-relatedness of the activities allowed us to categorise the activities and assist in our interpretation of the factor analysis output.

Materials

Activity Ratings. Ratings of the 32 everyday activities were generated using an online questionnaire. The questionnaire asks participants to rate on a 5-point Likert scale how much effort they typically exert when doing the activity; '*I put in a lot of effort when…*' *(Strongly Agree* to *Strongly Disagree*). They are also asked to rate, on a 5-point Likert scale, how motivated they typically are when doing the activity; *I feel motivated when I…'*, and the extent to which they have engaged in the activity during the past five years; '*In general, over the past five years I have…' (Several Times a Week* to *Never)*. Participants have the option to respond, '*Not Applicable',* in which case they were scored as *'Neither Agree nor Disagree'.* The sampling includes the following 32 activities: Calculate expenditure/budgeting, Inhibit negative emotions, Switch between tasks, Follow a GPS in an unfamiliar environment, Exercise, Clean, Grocery shop, Undertake personal maintenance, Plan your day, Work out solution, Feel self-confident, Recall childhood memories, Speak and listen in a noisy environment, Make sense of a dream, Read fiction, Play board games, Calm yourself, Tell a joke, Check the news, Wash up, DIY, Bake a cake, Pottery, Cook, Commute to work/University, Go to the loo, Laugh, Cry, Meditate, Artistic painting, Spend quality time with relatives, and Play an instrument.

Procedure

Data was collected via Qualtrics Survey Software (Qualtrics, LLC, Provo, Utah). The participants were asked about their age, sex, and what effort means to them from a pre-specified list: engagement, paying attention, being motivated, struggling, thinking a lot, getting tired, expending a resource, or exerting a force. The participants then completed the activity questionnaire, where the order of each activity within each effort, motivation, and engagement section was randomised.

Analysis

We performed exploratory factor analyses (EFA) on the effort ratings for a data-driven structure to emerge (AMOS 28 software; Arbuckle, 2014). The EFA on effort ratings was conducted using principal components extraction method with Promax rotation and extraction, based on an eigenvalue of at least 1. For interpretability purposes of the 32-item EFA, an additional EFA was ran with extraction restricted to four factors. We also suppressed items from the output with loadings less than .5. For all EFA factor loadings we report the pattern matrix. The EFA had a KMO = .72, and Bartlett's was significant (X^2(496) = 2357.96, p < .001), meaning that for basic assumptions of sampling adequacy and homoscedasticity were met.

To interpret the resulting factor structure in an objective fashion, we encoded each activity based on if it was rated by participants as being high or low in motivation, frequency, competency, and self-relevancy. To encode activities according to rated characteristics, the average rating for each activity was compared to the global average of all the activities for that characteristic. If the mean characteristic score for a specific activity was below the overall mean, the activity was categorized in the negative direction. For example, if the activity 'Cleaning' was rated below the overall mean for the characteristic 'Motivation', it was classified as 'Boring'. If a score was within ±0.1 of the mean, it was classified as 'neither'.

Results

Again, no single definition of effort stood out to the participants. They defined effort to imply engagement (*n* = 84), a force (*n* = 83), a resource (*n* = 65), and motivation (n = 60), with similar preference, with a slight emphasis on engagement. Others defined it as getting tired (*n* = 6), attention (*n* = 13), struggling (*n* = 13), and thinking a lot (*n* = 24).

The EFA of 32-items generated a ten-factor solution which explains 57% of the variance, with four of these possessing at least three items. When restricting the analysis to these four factors, the model explains 35% of the variance: first factor 16.2%, second factor 8.7%, third 5.5%, and fourth 5.0%. When encoding each activity according to participants' ratings of frequency, competence, motivation, and self-relevance, we see that the first factor loads on to competent acts (effort rating average 2.2). The second factor loads on to frequent activities (effort rating average 3.2). The third factor reflects rare, more challenging activities typically seen as hobbies (effort rating average 2.5). The fourth factor reflects internally focused, motivating, frequent activities the individual feels competent in undertaking (effort rating average 2.3; Table 1).

Table 1

Exploratory Factor Analysis of 32 Activities of Study 2B – Part Two

Construct/Items	Freq	Comp	Mot	Self	Factor Weight	M	SD
Effort							
Competent acts							
1. Wash up	O	A	M/B	E	0.79	2.51	1.07

2. Cook	O	A	M	S/E	0.75	2.10	0.97
3. Clean	R	A	B	E	0.64	2.17	0.90
4. Personal maintenance	R	A	B	S	0.59	1.98	0.93
5. Grocery shop	R	A	B	S	0.55	2.45	1.00
Frequent activities							
6. Laugh	O	A	M	S	0.78	3.10	1.30
7. Cry	O	D	B	S	0.68	3.07	1.17
8. Go to loo	O	D/A	M/B	S	0.64	3.33	1.31
9. Check news	O	D	B	E	0.58	3.38	1.07
Rare, difficult activities (hobbies)							
10. Pottery	R	D	B	S/E	0.71	3.07	0.68
11. Play instrument	R	D	M	E	0.59	2.08	1.30
12. Artistic painting	R	D	M/B	E/S	0.56	2.03	1.32
13. DIY	R	D	M	E	0.55	2.75	1.06
14. Bake cake	R	A	M	E/S	0.55	2.54	1.00
15. Play board game	R	D	M/B	E	0.55	2.78	1.06
Factor four							
16. Calm yourself	O	A/D	M	S	0.67	2.03	0.91
17. Feel self confident	O	A	M	S	0.55	2.53	1.12

Note. Freq = frequency (O = often, R = rare), Comp = competence (A = able, D = difficult), Mot = Motivation (M = motivating, B = boring), Self = self-relevance (S = internal self, E = external self), M = Mean effort ratings, SD = Standard Deviation of the mean, higher effort score indicates higher effort.

Discussion

The exploratory factor analysis reveals four factors based on effort ratings. As one of the drawbacks of EFA is factor interpretation, here we asked independent groups of participants to rate the activities according to how often they typically complete it, their competence when doing so, their sense of motivation, and the self-relatedness of the activity. We then mapped these ratings to each factor, to assess for patterns. All items of the first factor are activities that individuals feel competent to undertake. In other words, they are 'easy' tasks, with a tendency to be 'boring'. Here we find Wash-up, Clean, Cook, and Grocery shopping. The second factor groups activities that are done often, with a tendency to be self-focused, requiring a greater relative amount of effort. Here we find Laughing, Crying, and Going to the loo. The third factor reflects rare, challenging but motivating activities. These are typically hobbies such as Playing an instrument, Pottery, and Artistic painting. Finally, the fourth factor, which only consists of two items, so interpretation should be made with caution, reflects internally focused, motivating, frequent activities the individual feels competent in undertaking; Calm oneself and Feel self-confident. Thus, the two most consistent grouping variables are perceived competence, and frequency, with enjoyment playing a limited role in few instances. When correlating enjoyment with effort, the two concepts reveal a moderate relationship (R values spanning from 0.2-0.4), which is similar to Lyu & Gill, 2011. For future research, we note that, according to participants' reports, effort has a different meaning to different people. It is viewed mainly as either engagement, a force, motivation, or a resource. In addition, thirteen of the rated activities generated too widespread a variance on effort to form factors, which suggests that there are other aspects of effort yet to be captured, such as age, gender, or personality types.

Study 3

We used a task-based approach to measure effort willingness with an effort discounting procedure (Westbrook et al., 2013), and link this to enjoyment and competence ratings. Two versions of the task differed in enjoyment but were matched in other aspects that may influence motivation, such as duration, difficulty, uncertainty, and physical exertion.

Method

Sample

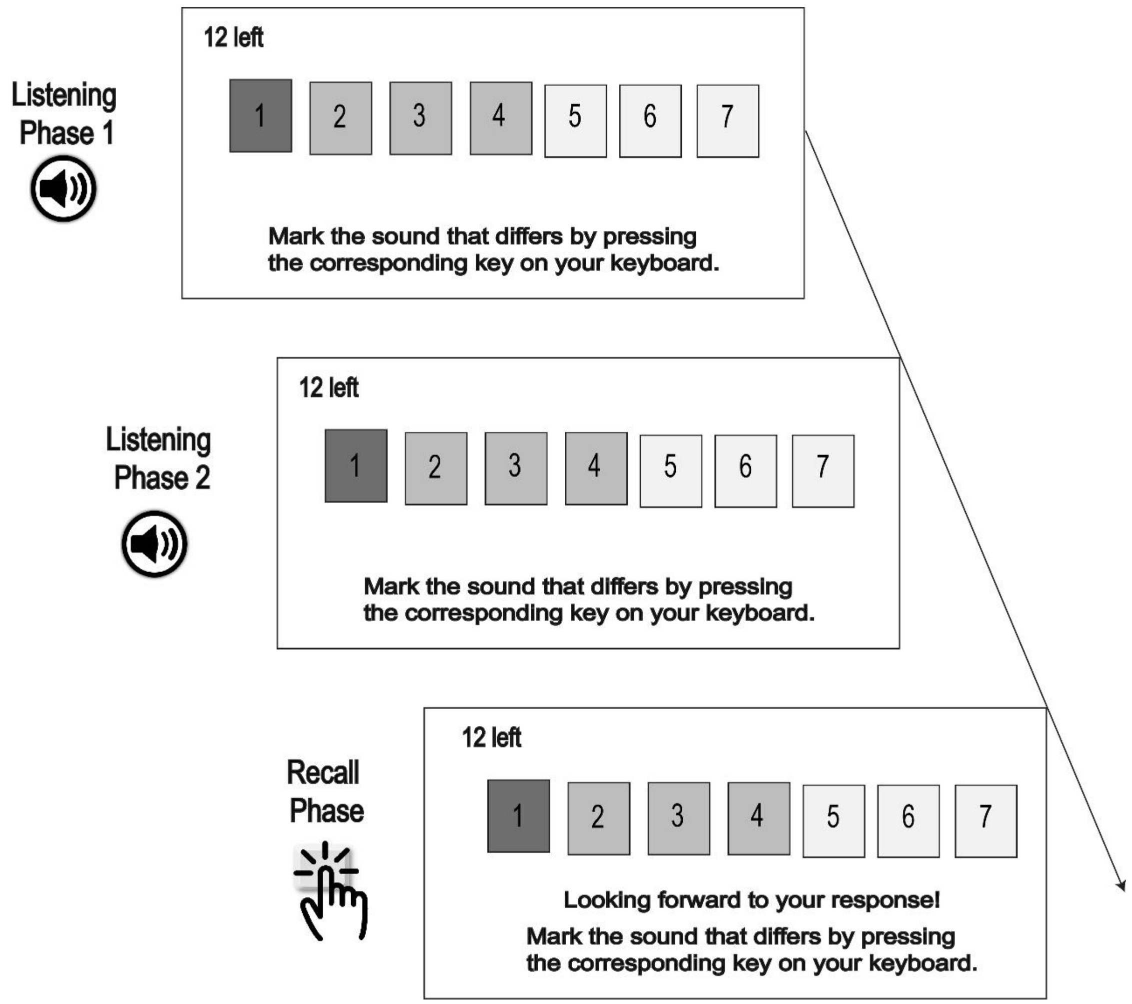
106 University of East Anglia Psychology students completed the study in return for course credits. 53 participants accessed the study online through a sign-up portal, while the other 53 completed it in the lab. The study was approved by the ethical committee in the School of Psychology, University of East Anglia, ID: ETH2223-0213.

Materials

Auditory Discrimination Task. The auditory discrimination task used was based on the Swedish Musical Discrimination Task as used in Study 1 of this thesis (Ullén et al., 2014, Figure 12). In our adapted versions, 12 trials were presented with increasing difficulty, starting with 4-tones sequences and going up to 7 tones-sequences, each difficulty level had two presentations. One of the sounds in a sequence pair differed. Respondents were required to determine which sound in the second sequence differed from the first using key presses corresponding to the ordinal number of the sound. The maximum number of sounds per string was capped at seven, as pilot data suggested that our typical population of students were failing to perform above chance for eight and nine string length trials. Each sound was 59ms in length, with 65ms between sounds, and two sequences separated in time with 1800ms.

Figure 12

Example of a Four Sound Trial for the Auditory Discrimination Task used in Study 3. During the Task, Participants Listened to a String of Four Sounds. The Squares Changed Colour When the Corresponding Sound was Played*. They Then Listened to a Second String of Four Sounds. One Sound in the Second Sequence Differed from the First, the Goal for the Participant was to Identify the Differing Sound Using the Numbers on the Keyboard. Participants Completed Three Trials of Each Difficulty, Which Ranged From 4-7 Sounds.*



Music-related version. Stimuli on the music-related version consisted of isochronous sequences of piano tones. The piano tones were used with permission from Ullén et al. (2014). The pitches ranged from C4 to A#5 (American standard pitch; 262-932 Hz).

Non-western Language-related version. Stimuli on the language-related version consisted of isochronous sequences of Zulu and *!Xσυ* clicks (Best et al., 1988; Best et al., 2003). The Zulu sound tokens used consisted of dental, lateral, and palatal clicks. The clicks were either pre-voiced, voiceless aspirated or voiceless unaspirated. The *!Xσυ* click stimuli consisted of bilabial, alveolar, dental, and palatal clicks. To balance task difficulty, a sound would only change to one of the same consonant type 1/3rd of the time. Otherwise, the sound would change more noticeably to a different consonant type.

For both versions, the sequences were graphically depicted as a straight horizontal line of squares which changed colour when the corresponding sound was played.

Effort-Based Decision-Making Task. The Effort Discounting Task was adapted from the methods used by Westbrook et al. (2013). Like Study 1, participants are asked to make a series of decisions between repeating an easier version of the auditory discrimination task for lesser reward, or a harder version for more reward. However, as two versions of the same task were used, we did not need to control for performance differences. Therefore, the easier task was always 4 sounds, and the hard 6. The reward was framed in terms of additional course credit. The base reward amount for the hard condition remained constant at 2 credits. The initial offer for the easy condition was half the offer of the hard (1 credit). The subsequent offers were titrated in the same way as Study 1. The offer for the easy condition following six choices was taken as the participants' effort score, which quantified the SV of the hard relative to the easy option. Possible SVs ranged from 0.01 (easy always chosen) to 1.99 (hard always chosen), with lower SVs indicating greater effort discounting.

Enjoyment and Competence Ratings. Participants made ratings on a 5-point Likert-scale to three statements relating to the listening tasks presented in randomized order. The statements were 'I found listening to these sounds enjoyable', 'I found listening to these sounds engaging' and 'I felt able to complete the task'. The scale ranged from 1 to 5, with higher scores corresponding to greater enjoyment, engagement, and perceived competence.

Depression. The 20-item Centre for Epidemiologic Studies Depression Scale (CES-D, Radloff, 1977) was used. On a 4-point Likert-scale, participants responded to statements such as 'I felt lonely' from Rarely or none of the time to Most or all of the time based on how they have felt during the past week. The scoring of positive items was reversed, with a score of 0-3 awarded for each response. All item scores were summed between zero (low depressive symptomatology) and 60 (high depressive symptomatology). A score of 20 is typically used as a cut-off for detecting subthreshold depression (Vilagut et al., 2016). A reliability analysis revealed a high level of reliability, with a Cronbach's alpha coefficient of .82. This indicates that the depression scale has strong inter-item correlation and that the scale is measuring the same underlying construct consistently.

Procedure

The study was run on PsychoPy (Pierce et al., 2019) and hosted in Pavlovia (www.pavlovia.org/#main). Participants reported the number of years they considered themselves to have been a musician. They then completed sound checks, followed by the two versions of the auditory sequence discrimination task in pseudorandomized order; one version being sequences of piano tones, the other one being sequences of Zulu clicks. At the end of each task version, participants rated task enjoyment, engagement, and competence, completed the effort discounting task, and completed one block of consequential trials. To increase the validity of the participants effort-based choices, they were told that one of their choices would be randomly selected to determine the difficulty of the consequential trials. Specifically, they were told they may have to repeat up to 10 more trials to receive the associated additional reward, and that they would only receive it subject to their response times and maintaining effort from previous trials. In fact, all participants were selected to repeat the same consequential trials for each version (three trials of 4-sounds sequences) and were awarded one additional course credit for doing so. Finally, participants completed the depression scale before being debriefed.

Analysis

The following analyses were conducted on both the online and in-person data, unless explicitly stated. To test for differences in participants perceived engagement, enjoyment, and competence ratings across the two versions of the task, we conducted a one-way repeated-measures ANOVA. This was followed up by Bonferroni corrected (p = .0167) post-hoc tests. We also conduct a paired-samples t test to check for differences in actual accuracy. As the distribution of SVs were non-normal (Music-related, W = .74, p < .001; Language-related, W = .72, p < .001), a Wilcoxon matched-pairs test was run to assess within-subject differences between effort scores for the two versions.

To understand how effort willingness for each version relates to perceived competence, engagement, and enjoyment, performance on consequential trials, music experience (years) and depression, we conducted a multivariate multiple regression with SVs for music and language-related tasks as the dependent variables.

To assess whether taking part online or in the lab influenced effort willingness, the data was split accordingly, and a one-way MANOVA between online and in-person for the music-related and language-related version was run. The dependent variables were SV, participant ratings and accuracy for both versions. Due to multiple comparisons, we accepted Bonferroni corrected statistical significance of p < .025 for the MANOVA main effect. Independent samples t-tests were used to further investigate the findings.

All statistical analyses were run in SPSS (IBM, 2020). Violin plots were created in RStudio version 4.1.3. We accept significance at p = .05 level, unless otherwise stated.

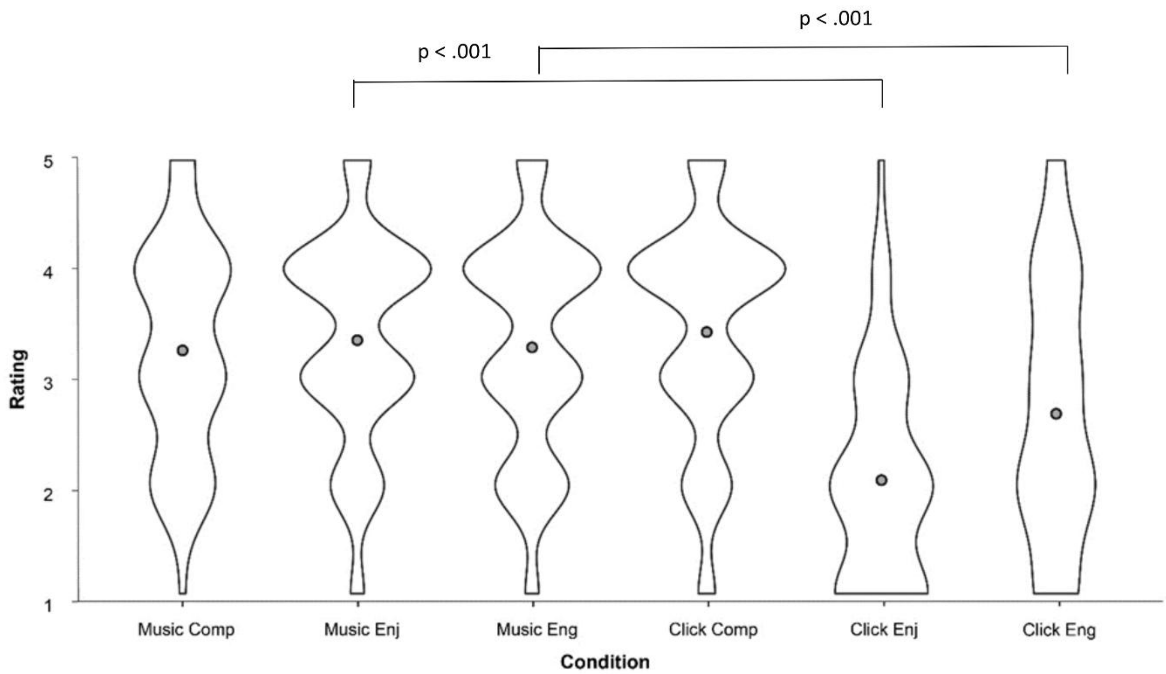
Results

Competence, but not enjoyment, engagement, music experience, or depression, predicts effort willingness

Participants' ratings significantly differed between task versions ($F(1, 104) = 44.09$, $p < .001$). Post-hoc analyses showed significant difference in enjoyability, $t = -10.85$, $p < .001$, with the music-related ($M = 3.34$, $SD = .96$) version being rated as more enjoyable than the language-related version ($M = 2.05$, $SD = .99$). There was also a significant difference in engagement ratings, $t = -4.86$, $p < .001$, with the music-related version ($M = 3.27$, $SD = 1.01$) being rated as more engaging than the language-related version ($M = 2.66$, $SD = 1.19$). There was no significant difference in perceived competence between the music-related ($M = 3.25$, $SD = .97$), and language-related ($M = 3.42$, $SD = .1.01$) versions ($t = 1.46$, $p = 0.15$; Figure 13). There was also no difference in actual accuracy for either version ($t(105) = 1.60$, $p = .11$). Despite differences in enjoyment and engagement, the Wilcoxon test of SV between the Music ($M = 1.62$, $SD = .51$) and Language ($M = 1.66$, $SD = .48$) versions showed there to be no significant differences in effort willingness, $Z = -.61$, $p = .54$.

Figure 13

Participant Ratings for Competence, Enjoyment and Engagement for Both Versions of the Sound Discrimination Task in Study 3



Note. Comp = Competence, Enj = Enjoyment, Eng = Engagement.

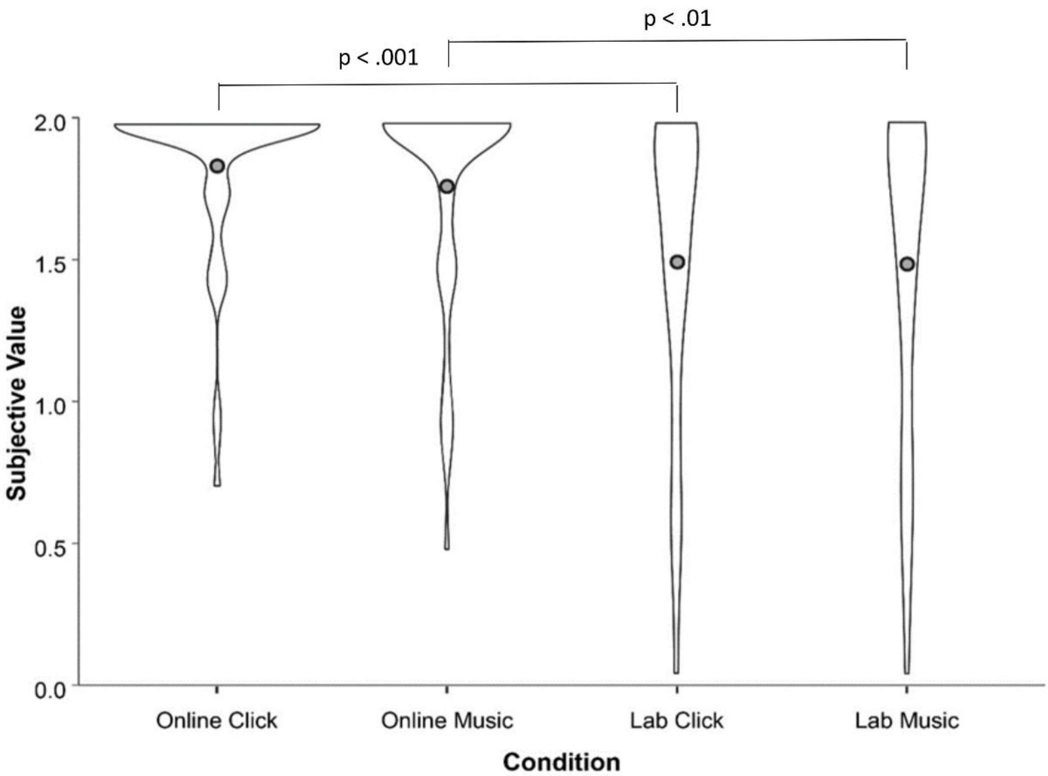
In line with this, the multivariate multiple regression model predicting SV for the music and language-related versions showed no significant effect for enjoyment or engagement for either task (p > .53). Instead, there was a significant main effect of perceived competence for the music-related task ($F(94)$ = 4.42, p = .02); perceived competence for the music-related task predicted SV for the music-related ($F(1)$ = 6.15, p = .02), but not the language-related task ($F(1)$ < .01, p = .99). There was no significant effect of perceived competence for the language-related task (p > .38). When it comes to actual competence, a significant main effect of accuracy for the language-related task was found (F (94) = 3.44, p = .04). The univariate tests showed that accuracy for the language-related version predicted SV for the music-related (F (1) = 6.81, p = .01), but not language-related version (F (1) = 3.16, p = .08) version. There was no main effect of accuracy for the music-related version on SV (p = .45). There was no main effect for either music experience (years) or depression scores (p < .38). A descriptive overview of the main metrics can be found in Table 2.

Online task results in higher effort willingness than in-person task

The MANOVA between SV online and in the lab showed a main effect of group, $F(2) = 2.65$, $p < .01$. This effect was driven by significant differences in both the SV for the music-related ($F(1) = 8.20$, $p < .01$), and language-related ($F(1) = 15.45$, $p < .001$) versions, and accuracy for each task respectively ($F(1) = 5.70$, $p = .02$; $F(1) = 4.06$, $p = .05$). Post hoc analyses showed the SV for the music-related task to be significantly higher online ($M = 1.76$, $SD = .39$) compared to in-person ($M = 1.48$, $SD = .58$; $t(104) = 2.86$, $p < .01$). This was also the case for the language-related version, with higher willingness online ($M = 1.83$, $SD = .30$), compared to in-person ($M = 1.49$, $SD = .56$; $t(104) = 3.93$, $p < .001$; Figure 14). Accuracy for the music-related task was significantly higher in the lab ($M = 2.42$, $SD = .75$) compared to online ($M = 2.02$, $SD = .95$; $t = -2.40$, $p = .02$). This was also the case for the language-related version, with higher accuracy in the lab ($M = 2.21$, $SD = .77$) compared to online ($M = 1.92$, $SD = .68$; $t = -2.01$, $p = .05$). There were no significant differences in perceived competence between online and in-person for either version (language; $t(104) = -.77$, $p = .50$; music; $t(104) = .20$, $p = .84$).

Figure 14

Subjective Values for Two Versions of the Sound Discrimination Task Across Online and Lab Participants for Study 3



Discussion

As expected, perceived enjoyment was higher for the music-related version, while perceived competence did not differ, nor did effort willingness. Notably, perceived competence predicted effort willingness for the music-related task, with higher perceived competence being related to higher effort willingness, while enjoyment did not predict effort willingness. When it comes to actual competence (performance) and effort, accuracy for the language-related task positively predicted effort willingness for the language-related version. This shows that effort is at times influenced by both perceived and actual ability, but not by affective aspects related to the auditory stimuli. Neither the number of years as a musician, nor depression, had any significant impact on effort willingness. We find interesting differences between data collected online versus in the lab. Firstly, effort willingness is greater online compared to in-person for both versions of the task. This is despite there being no difference in perceptions of enjoyability, engagement, nor competence. Secondly, we find a significant difference in accuracy between online and lab for both versions. Specifically, accuracy was higher in-person. Thus, the results show that despite performing worse online, participants were more willing to repeat the task for reward.

General Discussion

We find in our investigation of everyday activities (Study 2b– Part Two) that perceived task ability (competence) and how often a task has been undertaken (frequency), and to some degree self-relevance, matter for factor division. Furthermore, participants tend to exert less effort for competent acts than for frequent activities. In Study 3, we compared effort both within-subjects and within-task and find that competence, both perceived and actual, relate to effort willingness.

To find differing effects of competence and enjoyment is in line with the motivation literature showing an affective-competence distinction (Brubacher & Silinda, 2019; Pinxten et al., 2014; Timo et al., 2016). Enjoyment was found specifically to play a subordinate role in how factors were divided in Study 2b– Part Two, with only moderate correlations between motivation and effort scores. We also find that, whereas most items in factor one are classified as being perceived as boring, and the two items in factor four are regarded as being motivating, the other factors do not group by motivation primarily. When it comes to self-relevance, which could be regarded as an element of motivation (Ryan, 1982), we find a slightly clearer grouping in that factors two and four are made up of mostly internally-directed effort, and factor three is made up of external, more social, effortful activities. In Study 3, we expected the music-related version to be perceived as being more enjoyable than the language-related version, given that, at a population level, people are positively disposed to music (Kohut & Levarie, 1950; Sloboda, 2010), and that enjoyment is thought to reflect a key component of music engagement (Margulis et al., 2019). We find this to be the case through participant ratings of enjoyment and engagement, though these aspects did not significantly influence effort.

Our findings align with recent research showing no influence of sad mood induction on effort willingness in a general sample (Westbrook et al., 2022). However, they do differ with other research showing that general valence in everyday life influences effort intensity (Foo et al., 2009). The difference in findings may relate to the methods used, as in the effort discounting task used here and in Westbrook et al (2022) participants are given choices within-task where they could engage more or less intensely. Given that effort-based decision making is thought to occur for both identity and intensity (Shenhav et al., 2013), it may be that enjoyment matters more so in the real world when choosing what task to do (i.e., identity) when opportunity costs potentially are higher. Future factorial designs could assess the impact of enjoyment between tasks whereby effort-based choices relate both within and across tasks, similar to Embrey et al (2023; e.g., Would you rather repeat the 2-back for £1, or a 5-sequence anagram problem for £2?). This would tease apart whether enjoyment is more important when alternative tasks are available. Such a study could even also manipulate overall mood, to assess the interactions between overall mood and specific task enjoyment.

When it comes to competence and effort, our study shows that competence, both perceived and actual competence, matter for effort. We find that consequential trials related to effort choices. Specifically, the regression predicting effort from actual competence showed a main effect of accuracy for the language version, which predicted effort for the music-related version. Such findings align with Chong et al (2018), who showed that effort willingness increases with expertise. It is thought that not only does competence lead to high effort, but that high effort may also lead to greater competence over time. For example, Hales et al (2024) shows that rodents classified as workers make greater harder choices despite receiving harder offers. In humans, Forys et al (2024) show that even when adjusting for the difficulty of the offers according to the participants working memory ability on a visuospatial short-term memory task (as measured through training), greater working memory ability predicted a higher proportion of hard task/high reward versus easy task/low reward options chosen. Mækelæ et al. (2023) using the COG-ED, also found that higher performers discounted the cost of effort less, even when controlling for performance. Given that performance is higher for the high effort groups despite the tasks being harder suggests that estimations of expected value are influenced by the person's high effort willingness and not just their higher ability.

When it comes to effort and perceived competence, our exploratory factor analysis shows us that perceived competence explains our most dominant factor. Interestingly, participants reported themselves to put in less effort for activities they perceived themselves to be competent at. When looking at the activities in the first factor (e.g., washing up, grocery shopping), it is apparent that there may be a skill ceiling with these activities, such that increasing ability beyond a certain point may only serve to reduce perceived effort. Therefore, greater competence could still be associated with higher effort willingness despite lower self-perceived effort exertion. This view is complemented by the findings from our multiple regression, which shows that perceived competence for the music version exclusively predicts effort for the music version. Our findings align with the EVC (Shenhav, et al., 2013), which predicts that effort willingness is pulled in different direction depending on perceived ability. Specifically, if a person perceives that a behaviour is more likely to lead to reward (e.g., due to their increased ability), then they are less likely to discount the payoff associated with a behaviour (Frömer et al, 2021), leading to a greater expected value. It is likely that the affinity between perceived, and actual ability grow closer over time with experience, as value estimations are updated on an ongoing basis (Nagase et al., 2023).

Understanding how enjoyment influences effort is relevant for education, as high effort learning strategies such as memory retrieval and interleaved study are typically considered more effective than lower effort strategies (Brunmair & Richter, 2019). Therefore, understanding aspects that influence effort willingness is important for how to encourage students to undertake more effective effortful strategies (Janssen, et al., 2023). Here, we find evidence to suggest that both actual and perceived competence matter for effort rather than enjoyment, which is in line with research showing the importance of competence in influencing effort in schools (Barić et al., 2014). From a theoretical perspective, competency is thought to impact the likelihood of success and thus gaining reward, in line with the EVC (Shenhav et al., 2013). Our findings suggest that competence plays a larger role in estimations of EVC compared to enjoyment, as reflected by changes in SVs. This suggests that the enjoyability of potential actions in a decision context are less impactful on SV than competence. It could be that affective components indirectly influence effort-based decisions, by influencing perceived efficacy or the perceived value of the reward or cost, though this requires further testing. Competency may have also played a bigger role in the current design, as the study was in a work context where participants were being paid in credits to participate in the first place. Therefore, it may be that the importance of the enjoyability of the tasks was reduced due to the context of the decisions being made. It would be interesting to further understand how context influences the relevance or impact of task enjoyability on effort-based decisions. For example, does being in a social or more fun scenario influence the relevance of the enjoyment on effort-based decisions.

When it comes to experience, in Study 2b– Part Two, where we measure effort as retrospective estimations of effort put into various everyday activities rated by participants on a Likert scale, we find that effort categorizations can be understood in terms of frequency. This measure is a retrospective, average-based effort estimation over time of activities; many of which are mandatory and performed more or less daily. As such, they could be argued to represent, to a greater extent, a model-free (habitual) control of behaviour, whereby cost-benefit calculations are less explicit at any given time point (Westbrook & Braver, 2015). It has been suggested that mental feeling of effort is particularly explicit when costs are sufficiently high (Shepard, 2021; Westbrook & Braver, 2015), which agrees with the findings in Study 2b– Part Two showing that competent, everyday acts are rated as the least effortful.

In contrast, we find in Study 3, where we measure effort as estimations of the value of future monetary reward, no relationship between effort and experience. This is surprising given that we did not adjust the effort offers given to the participants based on performance, as we neither expected nor found differences in performance across versions. Therefore, if experience were to drive effort, this should be detectable in the current analyses. To find that experience does not relate to effort appears to contrast with Chong et al (2018), who found the slope of effort discounting for a physical task to be shallower for athletes compared to non-athlete controls, even when controlling for performance. However, they also found athletes were more willing at low load levels for an unrelated rapid-serial-visual presentation task that they had no experience difference for compared to non-athlete controls. Chong and colleagues argue that the changes in the athletes' responses could reflect changes due to experience. They posit that perhaps the athletes learnt the value of effort and so were perceived the costs even for a task unrelated to their expertise to be lower. This seems plausible considering recent research suggesting that effort contingent reward can influence the value assigned to effort itself (Clay et al., 2022; Lin et al., 2024).

An alternative but not necessarily mutually exclusive interpretation is that the differences seen were genetically driven. Therefore, could those with a global willingness to exert more effort be more likely to become athletes and drive between group effects? A twin study by Mosing et al (2014) supports this idea, as they show that certain abilities are not influenced by practice but are rather trait-like. They hypothesise that people may possess not only predispositions for certain abilities, but that this may drive willingness to put in effort for those activities. It may be that the non-musician sample used in the current study did not possess a great enough range of experience for it to influence effort willingness. Therefore, the question for future research is whether musicians show higher effort willingness in line with their greater ability; compared to participants without any years of musical training, and whether this effect is exclusive to the music-related task. If such an effect is found, but aspects such as enjoyability and engagement of the tasks are not mediated by musical experience, it could be inferred that such differences in effort willingness are driven by aspects such as the musician's innate ability and experience with music, rather than just because the music-related task was perceived as particularly more fun or engaging per se.

Understanding the relative contribution of experience and genetic predisposition is relevant in education and workplace settings, particularly with regards to effort training. For example, should we be rewarding effort (e.g., distributing grades or bonuses based on effort) rather than performance to increase later effort willingness? Understanding these aspects is also likely of clinical relevance, as recent studies show that effort willingness can return to baseline after remittance from disorders such as depression (Westbrook et al., 2022). Therefore, could proactive effort training interventions/experiences support recovery for disorders in which amotivation is a prominent feature?

When assessing the relationship between effort and depression as measured using the CES-D (Radloff, 1977), we find no significant relationship between the two. This is initially surprising given that depression is thought to reduce reward sensitivity (Cléry-Melin et al., 2011) and has been shown to lead to lower effort willingness in both depressed and non-clinical populations with high depressive symptomology (Yang et al., 2014). However, our findings show that depressive symptomology does not relate to effort for a cognitive task in an unselected non-clinical sample. This supports previous research in healthy participants showing reduced willingness to expend physical, but not cognitive, effort for reward (Forys et al., 2024; Gaillard et al., 2020). Exactly why depressive symptomology seems to relate more so to physical effort rather than cognitive remains unknown, though understanding the types of effort that individuals with depression or anhedonia are willing to exert is worthwhile in explaining dysfunction that individuals experience in their daily life (Johnston et al., 2019).

For the first time, we show that effort willingness differs for equivalent online and in-person conditions. Unlike previous studies with online and in-person effort willingness measures (Embrey et al., 2023), we compared effort willingness between online and in-person subjects with identical conditions. We find participants more likely to select harder levels when taking part online for both the language and music-related versions, despite lower performance. This is despite no self-reported qualitative difference in enjoyability or engagement, and performance tending to be higher in-person. It is worth noting that the effort offers presented to participants were not adjusted based on performance, as we did not expect nor find differences in difficulty between the two versions, meaning that the greater effort willingness found online was not due to lower performance. Instead, we speculate that perhaps the online participants interpreted the perceived consequences and/or demand characteristics to be lower than in the lab. Future within-subjects designs with counterbalanced online and in-person testing sessions, with more in-depth post-study feedback would be useful to further elucidate these effects. Validating effort measures for online administration is worthwhile, given that effort willingness has been shown to relate to many different disorders (Culbreth et al., 2016; Volkow et al., 2011; Westbrook et al., 2022). Additionally, it has recently been argued that effort measures may be more sensitive to early changes in cognition that may not be detectable from typically used performance measures (Taptiklis, 2023).

Together, these findings show that competence and affective components play distinct roles in effort-based decision making, with competence taking a more dominant role. It may be that previous studies showing relationships between affective components and effort were non-causal and driven by competence. For example, Pinxten et al. (2014) found that when accounting for math competence, the unique component of math enjoyment not explained by competence had a small negative effect on achievement. Our findings suggest that when making explicit effort-based judgements of intensity, estimations of payoff and cost seem not to depend on affective components. Therefore, whether affect and enjoyment plays a role in the computation of expectant value particularly in terms of identity according to the EVC (Shenhav et al., 2013) requires further investigation. We find differences in effort willingness online versus in-person, which also warrants future work, given its emerging clinical relevance.

CHAPTER FIVE: DISCUSSION - WHAT HAVE WE LEARNT ABOUT EFFORT?

Introduction

It is currently an exciting time for the effort literature. Studies show that effort is a useful construct that allows us to more greatly understand both typical and atypical behaviour. While there are many outstanding questions in the literature as highlighted by recent reviews (Thomson & Oppenheimer, 2022), there are also many interesting opportunities and avenues of exploration available to the effort researcher.

Here, I began the thesis by diving into the plethora of ways in which effort has been defined. I find that effort is theorised to play an important role in motivation, by biasing the expected value of behaviour. I slightly deviate from current leading theory, by speculating that effort reflects a cost function that mediates the subjective costs of task engagement, rather than reflecting the cost itself. I then went on to explore the range of effort measures that have been developed from the brain to the heart, from self-report to decision-making paradigms.

Relevant to both how effort is defined, and how it is measured, is the topic of domain specificity. When it comes to definitions, many seem agnostic though tend to lean on cognitive efforts. When it comes to measures, a division is more explicit, though it is not clear whether the findings from cognitive effort (e.g., attentional, working memory, response conflict) can be applied to physical and vice versa. Whether cognitive and physical efforts rely on a shared or independent mechanism is yet to be thoroughly investigated. Understanding how different species of effort relate will greatly expand the generalisability of leading theory (Shenhav et al., 2013). Such work is also relevant clinically when developing accessible and generalisable effort measures as well as in education and the workplace when predicting effort for a range of tasks. Details of this application are discussed below.

Given the relevance of understanding how the two relate, I went on to conduct a study where cognitive and physical effort willingness was compared within-subjects, by adapting the COG-ED.

Therefore, in this study effort willingness was operationalised using outcomes of an adapted COG-ED task. Specifically, SV was compared for four tasks to understand if effort willingness could explain patterns of effort choice within-subjects. Adapting effort measures for other tasks has become increasingly common, such as for the EEfRT (Lopez-Gamundi & Wardle, 2018). However, this has been less so for the COG-ED, which is surprising given its popularity as a measure of cognitive effort. To date, the measure has been cited on Google Scholar over 500 times, and the COG-ED has been used in countless studies.

To complement this, I conducted a large sample survey to get a sense of effort in daily life, where I again tried to understand the role of domain in effort allocation. Self-reported effort in everyday life can be interpreted as an indirect measure of effort, as it arguably reflects the outcome of many different aspects. For example, an individual perception of how much effort they put into tasks in daily life is not likely only influenced by how they define effort, as we find can vary greatly, but also by several other factors, such as time, money, and social pressure. Nevertheless, if effort willingness were dependant on domain, then this should be present from participant ratings. Assessing the domain specificity of effort willingness using both an EDT and a large self-report sample is not common and is a key strength of the current design. Including both means that the benefits of the EDT can be enjoyed (i.e., sensitivity to individual difference, control of confounding variables, clear metric) while increasing the generalisability and ecological validity of our findings by including a self-report measure relating to a range of activities.

I then turned my attention to aspects that matter for effort willingness within a domain. Competence is hypothesised to be important for effort, however the difference between perceived and actual competence remains unclear. We also noticed that there is a divide in competence and affect in the motivation literature, and that this distinction did not seem to be reflected in the effort literature. Therefore, we were interested in testing this for effort specifically. To this end, we asked participants to rate their effort in everyday life for 32 common activities to get an overall sense of how effort could be understood when accounting for aspects such as enjoyability, competence, and domain. This data was used firstly in Study 2b – Part One to conduct a CFA on 8 of the everyday items, and then again in Study 2b – Part Two along with responses for an additional 24 items in Study 2b – Part Two. Finally, I measured effort willingness for two versions of the same auditory discrimination task using the EDT procedure, where the sound stimuli were more or less enjoyable. Half of the data was collected in-person, and half online, to also test for potential differences in effort willingness between these two modalities. The key findings from these studies will now be discussed.

Effort Does Not Divide According to Domain

We find support for understanding effort in terms of an amodal process across cognitive and physical domains. For example, we find consistencies in effort choice within individuals across cognitive and physical tasks, as well as similar differences in effort willingness within a domain as between domains. Thus, our findings suggest that effort willingness for cognitive and physical tasks are more alike than they are separate. In Study 1, we used two auditory sequence discrimination tasks, a physically demanding task, and a dual task. The study adds to existing research on the topic, as we show the potential for COG-ED to be adapted to two other cognitive tasks, the SMDT and AXB tasks, as well as a physical backpack task and a dual task involving the simultaneous completion of two single tasks. This progresses from other research showing that COG-ED can be adapted to measure within the cognitive domain (i.e., working memory and speech comprehension; Crawford et al., 2022), and that alternative effort measures such as the EEfRT can be adapted to a physical task (Lopez-Gamundi et al., 2018). Additionally, by including more than one cognitive task, as well as a physical task and testing within-subjects, we build upon studies comparing effort willingness for one single cognitive to one single physical task (e.g., Bustamante et al., 2023; Lopez-Gamundi et al., 2018). We also adjusted effort offers based on performance (and bodyweight for the backpack task), to avoid the potential confound of ability, which may be particularly influential when comparing effort willingness across cognitive and physical tasks (Chong et al., 2018).

However, in retrospect, the results of Study 1 may have been more straight forward to interpret had we included more than one physical task, such as a button press or hand grip as in other studies using a physical effort task (Chong et el., 2015). This would have allowed us to compare effort willingness both within and across domains for both cognitive and physical tasks. However, it must be noted that there is a trade-off in choice of physical task, as by using the backpack task, we were able to include a dual condition in which the backpack could be worn while completing the sound discrimination task. This allowed us to see that the simultaneous exertion of both tasks seem to load onto the same effort cost. It may be possible for future design to perhaps include a dual task condition whereby the physical task is the maintenance of a certain grip strength, though such a design would need to account for likely fatigue effects linked with physical exertion on effort-based choice (Hogan et al., 2020).

In hindsight, it would have also been useful to have repeated the effort offers for several load levels. For example, studies using the COG-ED typically ask participants to make six decisions over several levels, such as between 1-back and 2-back, as well as 1-back to 3, 4 and 5 back (e.g., 30 choices; Westbrook et al., 2013). In contrast, we used one reward amount pairing and required them to complete the staircasing procedure once with six questions only once per task. Having only six trials per SV also means that much of their SV is dependent on the first choice made, which largely defines the future choices. For example, if a participant were to choose the lesser option on the first choice, and the greater option thereafter, they would end up with an SV of .97, whereas someone who were to choose the greater option first of all could never score below 1.03. While this is not a concern over repeated pairings, it could be more impactful when only six choices are made. Contrary to this possibility however, we did find low levels of second choice switching, with only 10, 5, 13 and 17 participants switching from their first choice for the AXB (N = 93), Backpack (N = 93), Tonal (N = 93), and dual tasks (N = 92) respectively. This trend was also generally found in Study 3, where 29 and 26 participants switched from their first choice for the music and language versions respectively (N = 106). In addition, when looking more closely at those who did switch on their second choice (i.e., either from high effort choice to low, or vice versa), we find that in Study 1 only 4, 1, 4 and 4 participants stuck with this switch for all remaining choices for the AXB, Backpack, Tonal, and dual tasks respectively. This was again also the case for Study 3, where only 2 and 1 participant/s were found to stick with their alternative second choice for the music and language versions respectively. Together, these choice patterns suggest that participants made considered choices and that the choice scenario had appropriate granularity to allow for a range of effort choice behaviour to be exhibited.

Another potential concern with using one SV per task however is that we were not able to assess changes in SV over changes to decision context. This meant we were limited in our interpretations to the SVs across tasks, rather than metrics like area under curve (Myerson et al., 2001), which reflects a way of quantifying the gradual change in SV based on the manipulation of another variable, such as effort, where a greater area under discounting curve indicates lesser discounting in SV. Given that it has been shown that load may matter between cognitive and physical tasks (Chong et al., 2018), we should have included this in order to not only compare single SV across tasks, but also the extent of effort discounting. To counter this, in future I would either include multiple reward amount pairings (e.g., £2 or £4) with a view to use the area under curve as a measure of effort willingness, rather than a single SV. Future studies looking to assess the domain specificity of effort generally should also look to include multiple tasks within and across domains. For example, a study using two cognitive versus two physical tasks, that all provide a performance measure and where the same effort measure is used, would be a good place to start, as it would provide comparisons of effort willingness both within and across domains. The offers presented should be performance adjusted and be presented in counterbalanced order.

Subsequently, the lab study was complemented by online studies to which we applied confirmatory and exploratory factor analyses on effort ratings of several everyday activities. In the confirmatory analyses we divided effort ratings of everyday activities into typical physical activities and cognitive activities respectively, which didn’t generate a good model fit. Instead, the exploratory analyses revealed a grouping of effort ratings mainly based on how often an activity is being conducted, and how competent the individual perceive themselves to be in the particular activity. In fact, it has become clear to me that many common activities cannot clearly be classified into being either physical or cognitive, since most contain elements of both, e.g. actions such as laugh or cry, may not fit clearly into cognitive or physical buckets. To me, this strengthens the argument that there is no clear logic as to why the brain would control effort willingness and effort execution with separate processes for physical and cognitive aspects. This became particularly obvious in our efforts to increase the ecological validity by collecting data on a wide range of activities, outside the ones that are typically studied in the lab. Even when including an additional round of data collection where we specifically picked predominantly cognitive tasks, e.g., mental arithmetic, or predominantly physical tasks, e.g., hiking, we did not find strong evidence of a cognitive/physical divide.

The finding that the cognitive/physical divide did not hold weight is in line with behavioural studies showing moderate relationships in effort willingness between cognitive and physical tasks (Bialaszek et al., 2017; Bustamante et al., 2023; Lim et al., 2023; Lopez-Gamundi & Wardle, 2018; Morris et al., 2020; Ostaszewski et al., 2013), as well as studies looking at exertion of effort in everyday life that show moderate relationships (Green et al., 2007; Marsh et al., 2001; Trautwein et al., 2006). Our findings also align with Chong et al (2018) who assessed cognitive and physical effort willingness in athletes and non-athlete controls. Distinct patterns of effort choice were found between the two groups for the two tasks, where increased effort seen in the athlete group was present for both cognitive and physical tasks. Whether such differences stem from training or genetic differences is still up for debate and will be discussed in the 'experience section' below. For example, Chong and colleagues did find greater differences in effort between athletes and non-athletes particularly for the physical task, which may have been driven by the athlete's increased ability for the hand grip task used, rather than due to underlying differences in effort willingness between cognitive and physical tasks. To investigate this one would need to either more carefully control for ability such that performance was matched for athletes and non-athletes. Alternatively, you could conduct an effort training study in which you assess change on not only one alternative far transfer task within a domain as in recent studies (Lin et al. 2024), but multiple across domains. This is relevant, since if there exists a combination of amodal effort willingness processes and task ability specific factors, it may explain why we found moderate support for a cognitive and physical divide in one of our confirmatory factor analyses.

Our findings also align with theories of embodied cognition that speak against arbitrary division of physical and cognitive processes (Wilson & Golonka 2013), and with neuroimaging research showing that while cognitive and physical demands may activate separate brain areas, a domain general evaluation network exists to evaluate information for any candidate task, seemingly regardless of whether the information is inherently relating to cognitive or physical tasks (Chong et al., 2017; Schmidt et al., 2012). Theoretically, our findings inform the EVC (Shenhav et al., 2013), as they suggest that when deciding how intensely to engage in a task, the expected value assigned to a candidate task is not fundamentally biased depending on whether the task in question is cognitive or physical. This does not mean to say that information cannot be gathered from different brain areas depending on whether they are cognitive or physical, but rather that the estimation of value is conducted in a common evaluation system, likely in the vmPFC (Lopez-Gamundi et al., 2021).

Our findings do however appear to contrast with studies showing differences in effort willingness across domains. For example, Tran et al. (2021) found a significant difference in effort willingness for a cognitive and physical version of the EEfRT. Specifically, they found that lower willingness to choose the hard task for the physical version related to higher anhedonia in patients with major depressive disorder, with low cognitive effort willingness relating to lower life functioning. Such findings suggest that there are distinct motivation systems for cognitive and physical efforts. However, in this study, the EEfRT was used to quantify effort, which requires participants to consider the probability of reward when making choices, in addition to reward amount and task difficulty. Therefore, it could be that the differences in choice between cognitive and physical tasks were driven by differences in the way that the probability of reward is evaluated across domains in those with greater depressive symptomology, rather than due to fundamental differences in effort willingness for cognitive and physical tasks. This could be the case as lower effort seen in those with depression has been hypothesised to be driven by impaired reward evaluation and anticipation (Pizzagalli et al., 2008). In line with this notion, Tran et al (2021) found reduced sensitivity to reward information in those with anhedonia when making their choices about physical effort specifically. Therefore, while a lower proportion of hard tasks chosen may appear to reflect effort differences across domains, such effects may in fact be confounded by differences in reward estimations for cognitive versus physical tasks. More research is required assessing how reward sensitivity influences the expected value of cognitive versus physical tasks in those with depression. The topic of how effort and depression relate is a topic further discussed in the 'depression section' below.

Our findings also appear to contrast with Cormier et al. (2019), who measured effort over time using adapted versions of the Grit Scale (Duckworth et al., 2007) for school and sport, and found that effort over time for school related more closely to later school success compared to sport grit. It was hypothesised that higher initial grit for school in the beginning of their study led to students specifically putting more effort into school over the course of the experiment, driving greater school success at a later date. Importantly, they suggest that the students had different 'levels' of grit depending on the task in question, meaning they were more or less willing to put effort in over time for cognitive (school) versus physical (sport) activities. However, one alternative interpretation of the findings is that the students with higher grit scores already possessed higher ability for either school or sport, driving them to score higher in later tests of ability. Therefore, the differences in grit may have been driven by starting ability, rather than fundamental differences in the way that effort is allocated. This could be tested in future by replicating Cormier et al. (2019), but with a view to understand changes in ability relative to starting grit. For example, how does the change in performance over time look for a starting lower performer with high grit compared to a lower performer with low grit? Does the formers high grit in one area influence their performance in another? Such a study would tease apart whether there are in fact differences between the way cognitive and physical effort tasks are evaluated over time, or whether other aspects such as competence explain apparent differences in effort.

Finally, our findings appear to contrast with pilot data from Van As et al. (2021). While the sample size was low at 17, and so should be interpreted with caution, they found physical effort choices were impacted by previous physical, but not cognitive effort exertion. Such findings show that fatigue can influence cognitive and physical effort willingness differently. While at first this data may be interpreted as evidence in favour of a cognitive/physical effort divide, it in fact logically shows that the costs during the participants estimations of expected value weighed more heavily for physical tasks when participants were physically fatigued, leading to lower effort willingness for the physical task. This therefore does not mean that the participants had different cost estimation systems for cognitive and physical tasks, but just rather in this instance that the costs were higher for repeating the physical task following physical effort, rather than cognitive, leading to a preference for the cognitive task. Like the study by Tran et al (2021) above, this study too illustrates the importance of controlling for confounding variables across cognitive and physical tasks that can cloud interpretations of effort willingness comparisons across cognitive and physical tasks.

Understanding whether effort is processed in a physical/cognitive domain unspecific manner have important societal implications. Given that effort is clinically relevant beyond depression, for disorders such as schizophrenia and ADHD (Strauss et al., 2016; Volkow et al., 2011), it is plausible that effort measures will soon be used alongside performance-based assessment tools typically used in the diagnosis and evaluation of clinical disorders (Taptiklis, 2023). When such a time comes, it will be important to understand how generalisable the findings from one effort measure are to another. As well as increasing generalisability of future effort measures, understanding the domain specificity of effort may also increase their accessibility. For example, if effort willingness were understood to be amodal, then you could plausibly test effort willingness for a cognitive task in those unable to complete physical effort assessments (perhaps due to injury), and vice versa for a physical task in those cognitively unable in certain aspects. Understanding the domain specificity of effort is also potentially important in education. This is because an amodal effort would mean that students who try extremely hard in some subjects will have a higher baseline effort willingness for tasks in other domains. Therefore, they are likely to discount the associated costs of a new unrelated task (i.e., studying a different subject) more greatly than their peers, which would lead to a greater expected value for that task and thus increase their subjective perceptions of task value. While this by no means guarantees their success, it does highlight their potential for doing so, as they have a bias for discounting cost. For this reason, it could also be used in the workplace, in recruiting talent, considering people for roles outside of their current remit, and for designing work environments to suit people's effort willingness. Such applications do however require an understanding of the plasticity of effort willingness over time, which will be discussed in due course.

While we do not find support for dissociating cognitive and physical effort in the present thesis, future work assessing the relationship between effort for different tasks within-subjects should take care to account for the influence of potential confounding variables. Here, in Study 1 we controlled for the influence of ability by adjusting effort offers based on performance, to prevent this potential confound. We also accounted for the participants competence when interpreting the output of factor analysis when measuring effort using perceptions relating to everyday activities. However, as the COGED relies on offering external reward to calculate SV in Study 1, another variable that may influence correlations between SVs across tasks is reward sensitivity. Reward sensitivity is how motivated a person is by reward in their environment (Carver & White, 1994), and is important to control for, as similar choice patterns across tasks may be driven by the reward values offered and the difference between offers, rather than due to a common effort willingness. In an effort study where reward sensitivity was controlled for when measuring SV, Kramer et al (2021) found reward sensitivity not to be a significant covariate. Such a finding suggests that reward sensitivity was unlikely to have confounded the results of the present thesis. However, Kramer measured reward sensitivity using the reward responsiveness scale and drive scale from the Behavioural Activation System Scale (Carver &

White, 1994), a self-report scale where participants respond to statements such as ‘When I’m doing well at something, I love to keep at it’. Therefore, it is possible that such a scale was not sufficiently sensitive enough to detect differences in reward sensitivity in such a way that effort-based decisions would be significantly impacted. It would be interesting for future studies to seek to replicate the findings from Study 1, perhaps by varying reward amount pairings, where reward sensitivity is measured from choice behaviour. Like in the study from Kramer, this sensitivity could then be used as a covariate during analyses, which in this case would be when comparing several SVs. As pointed out by Westbrook and colleagues (2013), controlling for reward sensitivity provides greater confidence that comparisons of effort are meaningful. Such a viewpoint is particularly relevant in the present thesis, where factors such as reward sensitivity may influence the relationship between effort choice for different tasks within-subjects.

Enjoyment Does Not Influence the Perceived Cost of Effort

We find support for the notion that enjoyment does not influence effort-based decisions. For example, we show that when comparing two versions of the same listening task, where the one with music-related stimuli was more enjoyable than an equivalent version with language stimuli, effort did not differ between versions. In line with this, we found that neither enjoyment nor engagement predicted effort. Thus, our findings show that task enjoyability does not seem to drive effort willingness. This study builds upon previous research looking at affect and effort, as we manipulate the enjoyability of stimuli used during the auditory sequence discrimination task and so were able to compare effort within-subjects. For example, in the study by Westbrook et al (2023), participants made effort-based decisions after either watching either a sad or neutral movie, between-subjects. They found that affect did not influence effort willingness in the lab. Specifically, they found no significant differences in a typical population between those who watched the sad movie and those who watched a neutral movie. Interestingly, they found that those with depression increased their effort following the sad video, compared to a control group and a remitted group. How effort and depression relate, as well as how effort willingness may change over time is a topic (e.g., presumably for those going from depressed to remitted) to be further discussed in sections to follow. Together, these findings suggest that effort willingness is influenced by neither the current mood of the decision-maker, or the enjoyability of a candidate task in a typical population.

Additionally, by manipulating the sound stimuli, we were able to compare effort within-task. This avoided many potential confounds that may have influenced the participants effort willingness across tasks, had we for example chosen to compare effort for separate appetitive versus aversive tasks (e.g., time or difficulty differences). Therefore, by keeping the task the same and only varying the sound stimuli, we could more clearly understand how the change to sound stimuli of the two versions influenced effort.

Our findings speak against those from Foo et al. (2009), who found that general valence in everyday life i.e., being upset, enthusiastic or inspired, influenced effort as measured with everyday momentary assessments. Effort was measured as entrepreneurs self-reported effort towards their venture/business (i.e., venture effort). Such a finding suggests that general mood influences effort-based decision-making. While this appears to contradict the findings from Westbrook et al. (2023), it is important to consider that Westbrook and colleague manipulated mood with video that was 3-minutes long. While this experimental manipulation was successful in effecting mood, as evidenced by their findings from the depression group and the self-ratings of sadness, it is not clear whether the other sample groups experienced a large enough change in their mood for it to influence their effort willingness. They speculate that the video may have particularly impacted those with depression as it produces a desirable affective state, or perhaps because of the motivational consequence of a sad movie being far lower than sadness induced by their 'real' life. However, an alternative interpretation is that the three-minute video made those with depression sufficiently sad, which in turn led them to exhibit changes in their effort willingness compared to non-depressed groups who did not. This alternative interpretation is supported by the finding that those with remitted depression also did not show changes to their effort following the sad movie. When digging into this point, I discovered that Westbrook and colleagues were unable to distinguish between post sadness ratings by sample, suggesting that the movie did not make those with depression sadder by comparison. However, as per the supplementary material, the depressed individual's sadness ratings were the highest to begin with, and they still gave a higher average sadness rating post sad movie, though not significantly higher. This leaves open the possibility that those with depression experienced a level of sadness sufficiently high for it to have in impact their mood and thus effort willingness. Therefore, it could be that mood impacts effort willingness at a certain level that was not reached in neither the auditory tasks used in my research, or through the sad movie, though this is speculative and requires further investigation. An extension of the presently discussed lab study with the addition of more extremely appetitive and aversive tasks, along with self-reported mood would allow for these effects to be further elucidated.

When it comes to our ratings of effort and affect, we correlated effort ratings and NFC. These analyses were conducted as NFC reflects the extent to which people seek out effort rather than avoid it (Sandra & Otto, 2018), and we wanted to understand its relationship to motivation for effort in everyday life. We find that NFC does not correlate with effort willingness for daily physical activities. We did find a general correlation between NFC and the cognitive activities, though positively in one sample and negatively in another. This somewhat contrasts with Culbreth et al. (2019), who found that that NFC did not predict everyday effort, nor COG-ED (Westbrook & Braver, 2015) or EEfRT (Treadway et al., 2009) responses. Interestingly, they also found neither the COG-ED nor the EEfRT significantly predicted enjoyment with daily activities. This is in line with our exploratory factor analysis where we find that participant's enjoyability ratings played a limited role in explaining effort for everyday activities. Specifically, only the third factor of the exploratory factor analyses grouped by tasks that were fun but challenging hobbies such as playing an instrument and artistic painting. Taken together, our findings may highlight the separation of affect in terms of the task, and the individual. We find that the participants did not differ in how much effort they put in based on how enjoyable the task was. Arguably, this could be because you can be happy doing an unenjoyable task, and sad doing an enjoyable task. Therefore, our enjoyment rating did not capture the changes to mood, as in other studies (Foo et al., 2009).

Theoretically, given that enjoyment for a task did not matter for effort when measured using adapted versions of the COG-ED and weakly when measured using self-reported effort of everyday activities, our findings largely support the notion that affect towards a task does not matter for effort intensity. I specify intensity specifically, as in the EDT, the participants were required to choose between higher or lower intensity of engagement, where the identity of the two options was the same (e.g., trials of the auditory discrimination task). Therefore, we did not give people a choice between tasks of a different identity, such as in Wu et al. (2023), where participants were given the choice between completing the Stroop Task, or doing nothing (i.e., watching a computer complete the Stroop task). This was also done by Embrey et al (2023), who gave participants choices between tasks of a different type (e.g., 'Would you rather repeat the 2-back for £1, or a 5-sequence anagram problem for £2?'). Such choices may be closer to decisions faced in everyday life, where there are real opportunity costs associated with spending all your time on one task (Kurzban et al., 2013). In contrast, in our lab study, there was no opportunity cost difference in the choice, as the participants were required to complete one or the other. Our self-reported effort data was also based on the intensity of effort that participants exert, which did not group by enjoyment. As neither the intensity of effort that the participants are willing to, or estimate themselves to exert, are significantly related to how enjoyable the task is, we can therefore say that affect does not meaningfully relate to SV, at least when it comes to intensity calculations as understood by the EVC (Shenhav et al., 2013). We can infer therefore that affect generally does not alter the cost of effort, the perceived efficacy, or outcome for intensity estimations. It may be that affect matters for effort when it comes to the identity aspect of the EVC. Therefore, the initial choice to engage in a task may be driven by effort, rather than its intensity. It would be worthwhile for future research to understand the role of enjoyment for intensity versus identity related conditions. For example, one could construct factorial designs in which participants make choices not only between different difficulty levels, but also across tasks (i.e., between tasks). This would be particularly valuable in understanding the findings in light of the EVC and the role of enjoyability in the estimation of task value (Shenhav et al., 2013).

Understanding the role of enjoyment in effort willingness is worthwhile in education. This is because willingness to invest effort is thought to be important in educational settings. For example, much research shows that higher effort learning strategies such as memory retrieval and interleaved study, in which learning strategies are mixed, are more effective than lower effort strategies (Brunmair & Richter, 2019; Roediger & Butler, 2011). Therefore, understanding aspects that influence effort willingness is important for how to encourage students to undertake more effective effortful strategies (Janssen, et al., 2023). If enjoyment were found to influence identity but not intensity, it could be that schools primarily need to worry about fun to the point of task engagement, at which point it becomes less important for effort willingness. Practically, this could mean that once you get a student engaged in a task, they are not going to engage more intensely if it is fun. Therefore, fun is a tool to get people involved. This notion may give a more refined explanation for why gamification in schools and the use of fun as a tool is an effective way to engage children as well as adults in learning (Lucardie, 2014; Massey et al., 2005).

Both Actual and Perceived Competence Matter for Effort

According to the motivation literature, competence is an important aspect that is influenced by the individual and the task before them (Timo et al., 2016; Pinxten et al., 2014). This aspect is also featured in the effort literature, as performance efficacy is a core aspect of the EVC (Shenhav et al., 2013). In the model, if an individual perceives that their behaviour is more likely to lead to reward, then they are more willing to exhibit that behaviour (Fromer et al., 2021). This is thought to be because the expected payoff is less impacted by the likelihood that the outcome state will be achieved, leading to a higher expected value (Grahek, et al., 2020). However, the degree to which individual differences in ability influence effort-based decision-making is difficult to study. This is because it requires disentangling individual differences in ability from individual differences in effort on expected value. Therefore, to what extent is an individual consistently choosing a hard task over an easy alternative doing so because of their higher ability, versus their effort willingness to forgo cost?

We find that actual competence relates to effort when effort is measured using the EDT. Specifically, we find that effort willingness related to overall performance during the practice trials for both cognitive tasks, even when the offers were adjusted based on performance. To find correlations respectively, with a lack of/weak correlations in these measures across tasks suggests that effort may derive from estimations of ability specific to the task in question. This is further supported by the results from the mediation analysis showing that competence for the music task mediated the relationship between music experience and effort. Additionally, we found that performance for the music tonal task predicted 14% of the variance in effort willingness. In a separate study, we again found that competence for consequential trials related to effort choices. Specifically, the regression predicting effort from actual competence showed a main effect of accuracy for the language version, which predicted effort for the music-related version.

Many studies show that ability and effort closely relate. For example, studies show that effort willingness increases because of expertise (Chong et al., 2018) and previous positive performance outcomes (Vinckier et al, 2019). Interestingly, studies also suggest that competence may not only lead to high effort, but that high effort may also lead to greater competence. Hales et al (2024) show that rodents that choose more harder tasks are also more accurate compared to rats doing easier ones. In humans using the Cognitive Effort Task (Silveira et al., 2021), Forys et al. (2024), found like us, that even when adjusting the difficulty of the offers according to the participants working memory ability on a visuospatial short-term memory task (as measured through training trials), greater working memory ability predicted a higher proportion of hard task/high reward versus easy task/low reward options chosen. Difficulty was adjusted through the number of squares participants were required to colour match. This is supported by Mækelæ et al. (2023) using the COD-ED, where they found that higher performers discounted the cost of effort less, even when controlling for performance. Given that performance is higher for the high effort groups despite the tasks being harder suggests that estimations of expected value are influenced by the persons high effort willingness and not just their higher ability.

However, not all previous research appears to show that competence and effort relate. For example, when using a rodent version of the Cognitive Effort Task, Hosking et al. (2015) found no significant difference in task accuracy during a nose poking task between rats classed as 'workers' (i.e., higher effort willingness) compared to 'slackers' (i.e., lower effort willingness). Despite finding no difference, it is important to note that the finding is that there is no difference between a high effort rodent group completing a harder version of a task, and a low effort rodent group completing an easier version. Therefore, while they findings appear to support no difference between effort groups, they in fact demonstrate the ability of the high effort group to perform to the same level despite completing harder trials. Such findings can be interpreted as indirect support for the findings of the current thesis, where effort and performance related even when the offers used during the EDT were adjusted based on training trials, and when they are the same for all participants regardless of performance.

Upon reflection, the backpack task we chose to use did not yield a performance metric, which would have been useful when trying to understand the effect of competence and effort choice. For example, alternative physical effort tasks used in other studies of effort give outcome measures of performance, such as number of buttons pressed (Lopez-Gamundi & Wardle., 2018) and nose-pokes (Hosking et al., 2015). In contrast, we only ensured that the participants stood with the weighted backpack for the set duration (which everyone was able to do). It should be noted that the backpack task was deliberately chosen as it could be paired with either of the cognitive tasks to be performed simultaneously. Therefore, precisely because carrying the backpack did not take additional resources away meant that it could be completed with a cognitive task simultaneously. However, we could have added a true fourth task, one that was not a dual condition but rather button pressing or a task similar.

As well as actual competence, we also found that perceived competence related to effort. This is significant given that the data for those same participants did not divide meaningfully according to domain, nor enjoyment across the analyses conducted in Study 2b Part One and Two. Unlike actual competence that is based on an objective performance metric, perceived competence derived from participants own estimations of their ability for a task. While the two likely relate, and perhaps more closely over time as estimations of perceived competence are updated during actual task experience (Nagase et al., 2022), we included both to get a fuller picture of how effort and competence relate.

We show with exploratory factor analyses that perceived competence was the most dominant predictor of self-rated effort, with all the items for the first factor being activities the participants rate as feeling competent to undertake. Interestingly, participants rated themselves as exerting less effort for competent activities compared to frequent ones. This is likely to be caused precisely because of their higher ability. While it seems that those with high ability should have higher effort willingness, given that you can presumably only get so good at the tasks in question (washing up, grocery shopping etc), those with high ability likely work to 'get the job done' with the minimum outlay. In the following study, we found that effort willingness did not differ between the two versions for which there was also no difference in perceived competence. In line with this, self-reported performance for the music version related to effort willingness for the music version.

On perceived competence and effort, the literature shows moderate correlations between the two (Lyu & Gill, 2011). Other studies show that perceived ability may be updated on an ongoing basis during effort exertion in line with previous performance (Nagase et al., 2022; Shenhav et al., 2013). Such findings suggest that perhaps the difference in the strength of the relationship between effort and perceived or actual performance may be mediated by experience and strengthen over time as perceptions of ability become more informed. Together, our findings show that both actual and perceived competence matter for effort. To disentangle the relative contribution of effort willingness and competence, future studies should include multiple tasks. For example, Crawford et al (2022) tested effort for two adapted versions of the COG-ED and find that effort willingness operated the same regardless of ability. They argue that by including multiple tasks, you can distinguish between effort willingness from competence.

Understanding the role of competence for effort is relevant, and particularly so in education. For example, studies show that students who perceive themselves as more competent, irrespective of actual performance, put in more effort (Baric et al., 2014). Such findings suggest that fostering student's sense of perceived competence may be an effective way of increasing their effort and improving their actual competence in the long term, thereby further promoting further effort investment, in a positive sort of reinforcement cycle. Further research is required to more fully understand how perceived competence is updated over time in response to feedback, and how that relates to effort willingness. As recent research suggests that such updating may happen during task exertion (Nagase et al, 2022), it would be interesting to see track perceived and actual performance, and effort, multiple times over the course of an experiment.

Experience Does Not Directly Predict Effort

We find that experience with a task does not influence effort. From the lab studies, we find that musical experience nor music listening predict effort for any of the tasks, even those based off the SMDT, an auditory discrimination task (Ullén et al., 2014). It could be argued that we did not find an effect because we controlled for performance, meaning that those with more experience may have performed better and so been given harder task offers, thereby neutralising their experience. This appears to conflict with the findings from Chong et al (2018), in a study where they assessed the relationship between experience and effort. They found the slope of effort discounting for a physical task to be shallower for athletes compared to non-athlete controls, even when controlling for performance. Such findings suggest that experience does matter for effort, as the athletes greater experience and likely higher perceived competence seemed to drive their higher effort willingness. However, Chong and colleagues went on to also find differences in the shape of the discounting function for a cognitive task between athletes and non-athlete controls, with athletes more willing at low load levels. Given that the cognitive task was a rapid-serial-visual presentation task the neither the athletes nor non-athletes would have experienced before, how is it that the athletes pattern of effort choice was significantly different even for this task?

Chong and colleagues (2018) suppose that the differences in the effort discounting gradient and the shape of the function could reflect changes in effort willingness over time due to experience. Perhaps the athletes learnt the value of effort and so were less likely to see it as a cost for an unrelated task, as suggested may be possible by recent research looking at effort training (Clay et al., 2022; Lin et al., 2024). For example, in the study by Clay et al. (2022), they show that an experimental group given effort-contingent reward on a working memory task selected more demanding novel transfer tasks (math) without the prospect of extrinsic reward compared to controls. They argue that over longer periods of time, people can learn to assign a positive value to effort itself. Similar findings were also recently found from Lin et al (2024). Such findings complement those from Chong, as they predict that the rowers would demonstrate both near and far transfer effects due to changes in the athletes perceived cost of effort.

An alternative but not necessarily mutually exclusive interpretation is that the athletes possessed a greater global willingness to exert effort that makes them become successful athletes. Such an interpretation is in line with the findings of Mosing et al (2014) who found that music practice did not causally relate to specific musical ability (ear for music), despite over 10,000 hours difference in practice in some twin pairs. They also hypothesise that people may not only have predispositions for certain abilities, but also the propensity to exert further effort towards those abilities. Such findings suggest that the athletes possess a trait-like predisposition for high effort willingness and is in line with a recent registered report showing a trait-like domain general effort willingness (Crawford et al., 2022).

Whatever the underlying cause, we did not sample from musicians, and so it is plausible that we simply did not have a diverse enough range of experience to find an effect of experience on effort. We had planned on sampling from professional footballers to investigate the role of experience in those with true professions like Chong and colleagues (2018) sample of elite rowers but were unable to do so due to COVID-19. Future studies could investigate the impact of targeted interventions on effort willingness for athletes versus non-athletes across cognitive and physical domains. Such a study would be a combination of the study by Chong and the training studies by Clay et al (2022) and Lin et al (2024). In doing so, it could be tested whether the gap in effort willingness between controls and athletes closes over time with experience, when controlling for increasing performance, or whether effort is stable.

Interestingly, when we look to the ratings of everyday effort, we find that exploratory factor analyses sorts according to frequency. Upon reflection of these findings, I take them to show support for the two aspects of decision making as described by the EVC (Shenhav et al., 2013). This is because our measure, that reflects the intensity of effort engagement in everyday life, also groups by how often the effort is exercised. To me, this demonstrates the fact that effort-based decisions occur in terms of what to attend to (identity) as well as how intensely (intensity), and that these two may be related. For example, it is plausible that an individual with assigns a greater value to going to the gym every day is also likely to assign greater value to working out more intensely (e.g., running on the treadmill versus walking). To get a fuller picture of effort willingness that translates more closely to the EVC, it would be useful for future designs to measure effort willingness in terms of both identity and intensity, perhaps with a view to capturing a ‘global’ effort willingness that reflects both aspects. This could be achieved by conducting two bouts of the EDT, once when making choices within-task and once between tasks.

As current measures capture a snapshot of an individual’s effort willingness at one point, it would be interesting to see longitudinal designs assessing how it changes over time. Therefore, the focus of effort measures may extend from quantifying effort discounting at one time point, to also measuring plasticity of effort over time. Such a study would tell us whether effort training is fruitful endeavour.

This has the potential to expand the EVC (Shenhav et al., 2013), and understand how estimations of expected value and in particular estimations of cost and payoff change over time.

Understanding how effort changes over time and whether it can be trained has potentially widespread implication. In education and the workplace for example, current approaches primarily reward performance and not effort, which arguably contribute to general tendencies for effort avoidance (Kool et al., 2010). However, incentives based around effort, and not performance, may increase effort willingness. For example, one could distribute incentives such as grades and bonuses based on effort, rather than solely performance. Understanding how effort changes over time is also relevant for sport, in for example talent selection and athlete development. Focus could be placed on an individual's effort willingness and how hard they are working during training, rather than their current performance.

Changes to an individual's effort willingness over time may also be relevant clinically. This is because not only will we be able to assess how a snapshot of effort willingness relates to a snapshot of depression severity, but by understanding effort plasticity we may be able to assess and better predict future change. The study by Westbrook et al (2022) demonstrates the relevance of this point, as they show that those with depression have lower effort willingness than both never before depressed controls and those with remitted depression. Such findings suggest that not only does low effort willingness relate to higher depression severity, but that when depression severity lowers, so does effort willingness. This opens the door for proactively increasing effort willingness in order to reduce depression severity, particularly aspects of their impairment relating to amotivation.

Effort Willingness is Higher Online Than In-Person

As discussed, effort has clinical relevance, for example for schizophrenia (Culbreth et al., 2016), ADHD (Volkow et al., 2011), and depression (Westbrook et al., 2022). Given the growth of remote electronic health services (Kim & Xie, 2017), it is worthwhile to see whether effort measures can be administered online. However, this requires understanding the differences between these two modalities. At the current time, most studies use either physically effortful tasks (Lopez-Gamundi & Wardle, 2018; Treadway et al., 2009), or those that require specialist equipment (Richter et al., 2008), meaning that they are best suited for lab administration. Therefore, how effort willingness relates online versus in the lab remains largely unknown.

In the current investigations, we find significant differences in effort online versus in the lab for both versions of our task. Specifically, effort willingness was higher online compared to the lab for both versions, regardless of one being musical stimuli and the other being language related. This was despite the participants performing better in person for both versions. It is important to note that the offers in the EDT for this study were not calibrated based on performance, meaning that lower effort willingness in the in-person group was not driven by increased performance and thus harder offers. This adjustment was not made as we did not anticipate, nor find, differences in performance between the two versions within-subjects. We also found the differences to occur in both studies despite no self-reported qualitative difference in enjoyability or engagement between online and in person.

To date, only two studies have used online versions of effort discounting tasks. In the first study using online measures by Johnson & Most (2023), participants completed an online version of the EDT design, where the effort was the number of words required to be typed backwards. However, as they were interested in the dynamic between effort and time, as well as NFC, they did not manipulate online versus lab. In contrast, the second study by Embrey et al. (2023) did compare between-subjects and asked the first group to complete the COG-ED (Westbrook et al., 2013) in-person. In a subsequent online study, they required a separate group of participants to also complete the same effort discounting task, as well as an adapted version relating to a sequence task. However, this time participants chose between easy and hard options that varied not only in difficulty and reward (e.g., 2-back for £1 or 3-back for £2), but also in task-type. For example, ‘Would you rather repeat the 2-back for £1, or a 5-sequence anagram problem for £2?’. Therefore, the extent to which context (i.e., online or in-person) effects effort discounting could not be directly addressed. Therefore, equivalent online and in-person conditions are yet to be tested for effort discounting tasks.

It remains unclear why effort differed online and in-person. It is known that participants perceptions of how much the experimenter cares about their decisions can lower online unless carefully maintained (Gregori et al., 2018). It could therefore have been that the online participants judged the consequences of failure during the consequential trials to be less, hence increasing the SV of a higher effort option to an acceptable level. This is supported by the lower performance seen online for both versions of the task compared to in-person. However, with regards to interpretations, it is worth noting that we made between subjects’ comparisons when looking at online versus lab responses. Therefore, more studies are needed, particularly with within subjects’ designs, to draw firmer conclusions as to why online and in person effort willingness differs. Such research could also ask those participants to report the reasoning behind their decisions online versus in-person, to get a feel for the drivers of differences in effort-based decisions.

If it were again found that effort willingness was higher online compared to in person within subjects, a logical next step would then be to compare clinical and typical populations in a large online sample. For example, in relation to schizophrenia, a design like Culbreth et al (2016) could be devised where all responses were completed online for clinical and non-clinical populations. If the online measures were able to distinguish between the two in a similar fashion to how they were in the original study, this would motivate the use of such effort measures being used alongside established performance based cognitive assessment batteries (Cambridge Cognition, 2024).

Effort Does Not Relate to General Depressive Symptomology

When it comes to depression specifically, we find that depressive symptomology as measured using the CES-D (Radloff, 1977) did not correlate with effort willingness for either version of the auditory discrimination task. Therefore, those in a healthy population with higher depressive symptomology were willing to accept the same reward for task completion as those from the same group with lower depressive symptomology. This suggests that, at least for non-clinical populations with the cognitive tasks we used, that depression does not influence sensitivity to costs, rewards, or estimations of efficacy, all of which could have affected our SV measure.

The findings contrast with studies showing that depression reduces reward sensitivity, thus negatively influencing subjectively value and thus effort choices (Westbrook et al., 2020; Westbrook et al., 2019). So why then did we not find an effect? It may be as simple as our sample. Much of the previous research has compared those with depression to controls. For example, Hershenberg et al. (2016) used a progressive ratio task where participants were required to identify the large of two numbers several times and found that those with depression showed lower breakpoints than healthy controls. The previously discussed study by Westbrook et al. (2022) also shows greater effort discounting in those with depression compared to controls for the n-back task. Differences in effort willingness for clinical populations have also been shown to be present for physical effort tasks, such as button-pressing and hand grip (Cléry-Melin et al., 2011; Treadway et al., 2012) suggesting there to be a global difference in the way that those with depression evaluate the cost of effort.

Across two studies looking at the relationship between effort willingness and depression, Yang et al (2014) found that those with depression showed greater effort discounting compared to healthy controls. Importantly, they also found that effort willingness was reduced in the general population with high depressive symptomology compared to controls with low/no symptom score as measured on the Beck Depression Inventory (Beck et al., 1961). Such a study shows that not only are patterns of effort choice different for those with depression, but that they also differ in a typical population as a function of depressive symptomology. This finding is somewhat contradicted by a recent preprint from Forys et al. (2024), who, also using the BDI on a sample of students, found that symptomology did not predict likelihood of choosing a high cognitive effort/high reward option during an adapted version of the cognitive effort task (Hosking et al., 2015; Silveira et al., 2021). Given that Yang and colleagues measured effort willingness for a physical task (using the EEfRT) suggests that the null findings from

Forys and myself may be related to the combination of the non-clinical sample and cognitive tasks used. Forys did find that working memory mattered for effort, as did we, which opens the possibility that for cognitive tasks, any significant influence of depressive symptomology on effort may be masked by competence. In contrast, Yang did not find any difference in competence.

In future, studies should include a cognitive and physical task as well as a clinical and non-clinical sample. Studying the relationship between effort and depression is important, as amotivation is thought of as an important aspect of depression (Treadway et al. 2009). Therefore, by understanding how effort and depression relate may open the door to novel interventions for depression. If effort training were found to be effective for example, then further studies could be conducted looking at not only the effectiveness of effort training on effort willingness, but also the impact that this may have on those with depression.

Pain Tolerance Does Not Relate to Effort

Pain is often defined as 'an unpleasant sensory and emotional experience associated with, or resembling that associated with, actual or potential tissue damage' (Raja et al., 2020). While pain is mostly driven by automatic physiological mechanisms, it does also interact with cognition. The two are related. For example, effort can influence perceptions of later painful stimuli (Riotino et al., 2023). While exactly why effort is unpleasant is being debated (Shenhav et al., 2017), effort is often described as aversive. Phenomenologically, effort also feels unpleasant. Like pain, effort promotes the conservation of resources by acting a stop signal to preserve energy (Kool & Botvinick, 2018; Shackman et al., 2011). They can also both be overridden to a point by reward (Vlaev et al., 2009). Both pain and effort activate similar brain areas, particularly the ACC, lateral prefrontal cortex, and insular cortex (Shackman et al., 2011), and so may recruit overlapping processes.

In our study, we chose to measure pain tolerance using the cold pressor (Mitchell et al., 2004), rather than using thermal pads as used by others (Silvestrini & Corradi-Dell'Acqua, 2022; Vogel et al., 2020), as it gave us an overall measure of pain tolerance. Therefore, we were interested in a single pain tolerance metric, rather than manipulating pain as an experimental condition or priming participants with pain. As an additional aspect, we also included a subject rating of perceived painfulness. We found that neither time in water not subjective pain related to effort willingness in cost-benefit calculations for simple shorter cognitive and physical lab tasks.

Such findings appear to speak against other studies showing relationships between effort and pain. For example, in a study directly comparing the aversive properties of effort and pain, Vogel et al. (2020) observed that effort and pain can be traded off against one another, whereby participants will systematically choose between either completing a difficult cognitive task presumed to require effort, and pain. Importantly, a relationship between pain catastrophising, i.e., how threatening pain is perceived to be, and effort was found, whereby higher pain threat was associated with effort choices, and away from pain. However, such finding simply tells us that those who do not like pain are willing to put in greater effort to avoid pain. In contrast, our findings show that the way in which you evaluate the cost of effort for different tasks does not necessarily relate, at least when pain is measured as a tolerance and through subjective ratings using the cold pressor.

It is worth noting that by including the pain measure, we did inadvertently introduce a potential confound to our effort scores. This is because we asked participants to undertake the cold pressor task after completing at least two of the single effort tasks. This decision was made partly for practical reasons, as the cold pressor was unreliable at maintaining a set temperature, and so the decision was made to test if the water had reached the required temperature, which was usually by the time most of the study was complete. However, we were unaware at the time of studies showing that pain and effort can influence one another sequentially. For example, studies show increased pain perception following cognitive effort exertion (Silvestrini et al., 2019), as well as the impact of pain on subsequent effort (Silvestrini & Corradi-Dell'Acqua, 2022). It is hypothesised that the respective cost of both effort and pain influence one another. Therefore, we did not foresee that by not having the participants complete the pain potentially in between effort measures, and at different timepoints, may have introduced a confound that was not controlled for.

To improve our understanding of how pain interacts with cognitive processes (Bushnell et al., 2013), future studies should exercise caution when subjecting their participants to pain to prevent pain confounding effort choices, sticking to a fixed time, ideally after effort choices have been made (if effort is the primary construct of interest). Studies could even separate out the pain administration collection into independent testing sessions. Researchers interested in the relationship between effort and pain specifically could compare multiple measures of pain within-subjects to assess their relationships to effort willingness. By conducting a study about lots of pain and effort, it would be possible to elucidate which aspects of willingness to endure pain relate to effort. For example, is it duration as in the cold pressor (i.e., individual differences in pain tolerance), or thermal stimulation as used by Silvestrini and colleagues (I.e., individual differences in the perceived cost of pain)? One would have to control for aspects such as order effects, by measuring effort first and counterbalancing the order of the subsequent pain measures.

Ethical Considerations

The research conducted in the present thesis was conducted in according with permission from the UEA Psychology Ethics Board. The board aligns itself to the BPS Code of Human Research, which is considered the gold standard in terms of guidelines for Psychology research ethics in the UK. As such, the research herein complies with the key aspects of the code, such as consent, confidentiality, debrief, information handling and researcher/participant dynamics. Due to my adherence to the UEA ethics process, there have been few ethical or moral issues in the present project.

The only noteworthy deviation from the ‘typical’ ethics process throughout the course of my research was during COVID-19 social distancing. Due to the virus, I was required to devise and submit socially distanced procedures for which to run Study 1. This included but was not limited to ensuring that the participant and I were negative on tests, cleaning all equipment, wearing masks, and amending the procedure to maintain distance.

Thesis Summary

This thesis investigated the role of domain, competence and enjoyment for effort, using both adapted effort discounting tasks, as well as self-reported effort. Here, I have defined effort as a cost function that influences the 'costliness' of candidate tasks during the process of value calculation according to the EVC (Shenhav et al., 2013). This deviates from leading theory in that I view effort as a function that evaluates cost, rather than as a cost itself. I propose that the 'cost' is entirely task specific, the nature of which changes depending on the task at hand.

In line with this, for the first time we show that effort willingness is consistent within and between domains, including for a dual task. Interestingly, neither pain tolerance nor music experience predicted effort, but task specific competence did, and to an extent general ability (intelligence). Ability was also found to mediate the relationship between experience and effort. Such findings suggest that experience is not causally related to effort, but may increase perceptions of ability, which in turn increase effort willingness (Study 1). This was followed up by collecting two large online samples where we asked participants to rate effort for 8 common daily activities, where we found weak support for dividing responses according to cognitive or physical (Studies 2a, 2b – Part One). This was followed up by a new set of ten everyday tasks that were rated by the participants as being cognitive or physical. We find weak support for dividing effort to domain and find no stronger covariance between cognitive and physical tasks respectively (Study 2c). We then expanded our tasks to 32 and conducted exploratory analyses of what aspects matter for effort. We find that the factors group by competence and frequency, and to a lesser extent how fun tasks are. (Study 2b– Part Two). To further investigate the role of competence and enjoyment, we then tested effort within a domain by manipulating the enjoyability of sound stimuli. We find that differences did not lead to differences in effort choice. Instead, effort was again related to competence, both perceived and actual. Experience was again not predictive of effort, though we did find that responses significantly differed between online and in-person conditions, with greater effort willingness online despite lower performance (Study 3).

This thesis explored multiple elements relevant to effort-based decision making between and within domains. In the present thesis we do not find support for value estimations during decision-making being driven inherently by domain. While further research is required to test the possibility of a wholly domain unspecific effort willingness, we find that differences in effort choice seem to occur irrespective of domain. Notably, innovative work presented in this thesis provides valuable insight into the role of competence in driving effort choice and judgements. It is likely that an individual's baseline effort willingness interacts with task specific factors to drive decision-making, though such a domain unspecific effort requires further support and validation. We also find the limited roles of enjoyment and experience and highlight the relevance of adapting effort measures for online administration. Understanding these aspects better is truly a worthwhile endeavour, with the potential to take effort from simply a cost that to be paid, to an important variable in understanding decision-making and thus people's behaviour more widely.

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