Unifying Cognitive Effort Allocation in Value-Based Choice and Cognitive Control

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Brief Abstract in English

Why do the decisions we make sometimes feel quick and effortless while other times long and effortful? My thesis explores the feeling and exertion of mental effort in both objective and subjective decisions. Recent models posit that mental effort is invested when the costs of exertion are associated with commensurate rewards. Yet, to better understand the predictions of cost-benefit models of effort, we first need to establish measures of momentary effort exertion while deciding. In the first experiment, we test whether task-evoked pupillary responses reflect momentary effort exertion while performing an objective decision-making task and track both individual differences in effort costs and reward-induced effort modulations. We observe that pupillary responses during objective decision-making tasks do indeed track individual differences in effort costs and momentary reward-induced changes in mental exertion. Next, we test whether strategic conflict in value-based choices engenders feelings of mental demand. We find that participants reliably rate value-based decisions with higher levels of strategic conflict as more demanding. Next, aligned with the predictions of cost-benefit models of effort, we test whether these decisions rated as more demanding are systematically avoided using a demand-selection paradigm. Our results confirm that demanding value-based choices are reliably avoided when given the option. Finally, we sought to test whether demanding value-based choices elicited greater pupil dilation and to what extent the observed effort avoidance could be explained by individual differences in momentary effort exertion, indexed by pupillary responses. To our surprise, we find that demanding value-based choices elicited smaller pupil dilations and that the individuals with smaller pupillary responses to demanding value-based choices avoided the demand in a secondary task phase. Aligned with the marginal value of effort, these results suggest that participants withdraw their effort when exertion offers no additional

benefits to task performance. Together, the results of these studies suggest that pupillary responses can serve as a reliable measure of effort exertion in both objective and subjective decisions and that the cost-benefit model of effort can serve as a unifying framework to understand effort across both objective and subjective decisions.

Résumé en Français

Pourquoi les décisions que nous prenons nous semblent-elles parfois rapides et sans effort alors qu'elles sont parfois longues et laborieuses? Ma thèse explore la sensation et l'exercice de l'effort mental dans les décisions objectives et subjectives. Des modèles récents suggèrent que l'effort mental est investi lorsque les coûts de l'effort sont associés à des récompenses proportionnelles. Cependant, pour mieux comprendre les prédictions des modèles coût-avantage de l'effort, nous devons d'abord établir des mesures d'effort momentané lors de la prise de décision. Dans la première expérience, nous testons si les réponses pupillaires provoquées par une tâche reflètent l'effort momentané lors de l'exécution d'une tâche de prise de décision objective et suivent à la fois les différences individuelles dans les coûts de l'effort et les modulations de l'effort induites par les récompenses. Nous observons que les dilatations pupillaires lors de tâches de prise de décision objective suivent, effectivement, les différences individuelles dans les coûts d'effort et les changements momentanés de l'effort mental induits par les récompenses. Ensuite, nous testons si le conflit stratégique dans les choix économiques engendre un sentiment d'exigence mentale. Nous constatons que les participants évaluent constamment comme étant plus exigeantes les décisions basées sur la valeur qui présentent des niveaux élevés de conflit stratégique. Ensuite, alignés sur les prédictions des modèles coût-avantage de l'effort, nous testons si ces décisions jugées plus exigeantes sont systématiquement évitées à l'aide d'un paradigme de sélection de la demande. Nos résultats confirment que les choix économiques les plus exigeants sont évités davantage lorsque nous donnons l'option d'éviter aux participants. Enfin, nous avons testé si les choix économiques exigeants provoquaient une plus grande dilatation pupillaire, et dans quelle mesure il existe une relation entre les dilatations pupillaires et le choix d'éviter l'effort. À notre grande surprise, nous

constatons que les choix plus exigeants ont suscité des dilatations pupillaires plus petites et que les individus ayant des réponses pupillaires plus faibles aux choix exigeants ont évité davantage les choix exigeants dans une deuxième phase. Alignés sur la valeur marginale de l'effort, ces résultats suggèrent que les participants réduisent leur effort lorsque celui-ci n'offre aucun avantage supplémentaire à l'exécution de la tâche. Globalement, les résultats de ces études suggèrent que les réponses pupillaires peuvent servir de mesure fiable de l'effort dans les décisions objectives et subjectives, et que le modèle coût-avantage de l'effort peut servir de cadre unificateur pour comprendre l'effort à travers les décisions objectives et subjectives.

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Contribution to Original Knowledge

The last decade of research in cognitive science has seen a rise in interest in better understanding humans' allocation of cognitive resources to goal-directed tasks referred to as mental effort. Recent theories have suggested that mental effort allocation follows a cost-benefit trade-off whereby the decision to expend effort is determined by the costs associated with effort exertion, the rewards for successful task completion and their associated probabilities (Frömer et al., 2021; Kool et al., 2010; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018). Yet, research on mental effort has been limited by researchers' ability to measure the amount of effort invested in a task. This is particularly true for tasks where there is a non-monotonic relationship between effort investment and task performance like value-based decision-making. While there exists evidence that momentary changes in pupil diameter may reflect online effort investment, it remains unclear whether this measure reliably indexes within-person variation in effort investment (van der Wel & van Steenbergen, 2018). Furthermore, little research has sought to bridge the study of mental effort exertion in cognitive control tasks where responses are based on external criteria and value-based decision-making tasks where responses are based on internal criteria. Thus, it remains unclear whether these cost-benefit models of effort investment can serve as theories of effort allocation in both domains.

The overarching aim of this thesis is to resolve these open questions and bridge cognitive control and value-based decision-making research by determining whether pupil diameter can be used as a viable index of mental effort exertion. To this end, I designed four experiments to address this lacuna and better understand cognitive effort exertion in cognitive control and value-based tasks.

The first study (Chapter 2), published in Cognitive Affective Behavioral Neuroscience, is the first to examine whether pupil diameter can be used as a reliable index of within-person pupil effort exertion within-person. To test this, we leveraged the cost-benefit model of effort exertion (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018) and asked participants to complete a cognitive control task under three reward conditions while measuring the fluctuations in their pupil diameter. The results indicate that participants' pupils were indeed larger for more difficult tasks, larger for those who performed better at the task, and larger for those who showed greater reward-induced performance changes.

The second study (Chapter 4), which has been prepared for submission, is the first to examine whether demanding value-based descisions are avoided as predicted by the cost-benefit model. Similarly, this study is the first to use pupil diameter to index effort exertion in value-based choice and relate this to individual differences in demand avoidance. To test this, we developed and validated a novel task to measure demand avoidance in value-based choices. Across two experiments, the results indicate that participants overwhelmingly avoid demanding value-based choices and that individual differences in effort exertion are predictive of later demand avoidance. Together, these studies are the first to bridge the study of mental effort in both cognitive control tasks and value-based decision-making, suggesting that common methods and theories can be used to understand the deployment of mental effort across task domains.

Contribution of Authors

For the first manuscript in Section 2, Kevin da Silva-Castanheira co-conceived the initial research question, co-designed and programmed all experiments, co-collected and analyzed data, and co-authored the manuscript. S.L. co-designed the experiment, co-collected the data, and edited the manuscript. A.R.O. supervised the project, co-conceived the initial research question, co-designed the experiment, secured funding, and co-authored the manuscript.

For the second manuscript in Section 4, Kevin da Silva-Castanheira co-conceived the initial research question, co-designed and programmed all experiments, collected, and analyzed data, and co-authored the manuscript. A.R.O. supervised the project, co-conceived the initial research question, co-designed the experiment, secured funding, and co-authored the manuscript.

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List of Abbreviations

Abbreviation	Meaning
ACC	Anterior Cingulate Cortex
AOI	Area of Interest
BAS	Behavioural Approach System
BIS	Behavioural Inhibition System
CI	Confidence Interval
DAT	Decision Avoidance Task
DST	Demand Selection Task
EF	Executive Function
EIP	Elementary Information Processes
EV	Expected Value
JDM	Judgement and Decision-Making
NASA TLX	National Aeronautics and Space Administration-Task Load Index
NFC	Need for Cognition
RT	Response time
SD	Standard Deviation
SE	Standard Error
STAI	State-trait Anxiety Inventory
TEPR	Task-evoked Pupillary Response

Section 1: Introduction & Comprehensive Review of the Relevant Literature

Humans make decisions daily, each associated with its own respective subjective feeling of demand. Extensively researching and deliberating between investments intuitively feels more effortful than flipping a coin or phoning a friend. Yet, why we sometimes decide to use more effortful decision strategies while other times rely on fast, habitual strategies remains unclear. On the one hand, humans avoid *cognitive effort*—using cognitive resources (e.g., attention, working memory) in service of a goal (Kool et al., 2010)—and will even opt for a painful stimulus over the prospect of exerting cognitive effort (Vogel et al., 2020). Yet, on the other hand, individuals often must engage in effortful goal-directed behaviour to obtain rewards. For example, a carefully selected investment offers the opportunity to reap large returns. Consequently, our decisions to expend (versus withhold) mentally effortful behaviours, often presents a conflict between two opposing goals: minimizing the associated effort costs and maximizing rewards. On this view, prominent theories of effort investment posit that our decision to expend (or withhold) cognitive effort requires the integration of the benefits, the costs, and the likelihood of successful performance (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018). In fact, the prospect of performance-linked reward incentives has been found to motivate effort investment across a breadth of cognitive domains including task-switching (Sandra & Otto, 2018), response inhibition (Chiew & Braver, 2014), working memory (Beck et al., 2010), and episodic memory (da Silva Castanheira et al., 2022; Shohamy & Adcock, 2010) to name a few. However, while there is a plethora of work suggesting the decision to exert cognitive control follows a cost-benefit trade-off, there is comparably less work showing that these models also apply to value-based choices. Thus, the goal of my proposed research is to unify our understanding of effort investment in both cognitive control (i.e., *how do I adjust my information* *processing to achieve my goals?*) and value-based choice (i.e., *how do I weigh costs and benefits to choose?*) using Cost-Benefit models of effort investment.

A burgeoning body of literature suggests that people integrate costs and benefits when deciding to exert cognitive control—increasing benefits encourage effort investment while increasing costs discourage exertion (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018). Supporting this view, reward incentives have been found to motivate effort investment (Botvinick & Braver, 2015; Westbrook & Braver, 2015), particularly for those with large effort costs (da Silva Castanheira, LoParco, et al., 2021; Sandra & Otto, 2018) and rewards associated with greater effort are less valued (Chong et al., 2017; Westbrook et al., 2013). Thus, all else being equal, cost-benefit models predict that effort exertion should be avoided as the associated costs of deploying cognitive resources are not offset by benefits. While these predictions are generally aligned with models of effort exertion in value-based choice, cost-benefit models have largely gone untested when studying value-based decision-making. In large part, the literature on cognitive control and value-based decision-making has developed in parallel with few attempts at developing an integrated account of effort.

Our understanding of effort in value-based decision-making has largely stemmed from the Judgement and Decision-making (JDM) literature which is focused on the reduction of effort: the heuristics and biases approach (Tversky & Kahneman, 1974), and the fast and frugal approach (Gigerenzer & Todd, 1999). Both approaches explain how our preferences emerge from the use of limited cognitive resources which often leads to violations of economic norms. Classical Economic theories posit that decision-makers should maximize Expected value (EV)—the mean outcome one should expect from selecting an option. Following the predictions of Rational Choice Theory should lead to forward-looking choices that maximize EV (Von

Neumann & Morgenstern, 1947). Yet decision-makers, even with complete information about the consequences of their choices, often deviate from these norms. For example, people will violate transitivity (Allais, 1953), violate the description invariance axiom by being sensitive to the framing of an option as gains or losses (Tversky & Kahneman, 1981), or even be influenced by previously incurred costs (Thaler, 1980). The heuristics and biases approach sees these violations as the downstream effects of withholding effort exertion when deciding via the use of simplifying decision strategies (i.e., heuristics; Thaler, 1980; Tversky & Kahneman, 1974).

The Fast and frugal approach, however, suggests that decision-makers' use of these heuristics not only reflects the minimization of effort (i.e., time and resources) but also the maximization of task performance (Gigerenzer & Todd, 1999; Goldstein & Gigerenzer, 2002; Todd & Gigerenzer, 2007). In this framework, using heuristics does not invariably lead to biases, but can sometimes outperform other more deliberative approaches depending on the task environment (e.g., time pressure, available information).

Together, these frameworks fall under the broader category of Dual process theories of decision-making which contrast effortful to effortless decision strategies (Diederich & Trueblood, 2018; Evans, 2003) in which withholding effort is interpreted as either reflecting the limitations on cognition or reflecting the frugal use of cognitive resources. Yet, defining the boundary between the two systems based on first principles has proven difficult (De Neys, 2021; Dewey, 2021; Evans & Stanovich, 2013). Perhaps, for this reason, a separate line of work has focused on the effects of the quantity rather than the quality of the information processed.

The Information-processing approach offers a third framework to understanding effort in decision-making. While Dual process accounts focus on the use of distinct cognitive strategies which require different levels of cognitive control to implement, the information processing approach assumes that choices follow a speed-accuracy trade-off (Payne & Bettman, 2004). In this framework, preferences are constructed via the time-consuming sampling of evidence in favor of an option either from the environment (Busemeyer, 1993; Busemeyer & Townsend, 1993; Payne et al., 1993; Roe et al., 2001) or memory (Lieder et al., 2018). Once a decision-maker reaches a pre-specified level of evidence in favor of an option, the preferred option is chosen. Critically, the amount of evidence needed before deciding is a free parameter that controls the Speed-Accuracy trade-off: a high threshold will lead to slow and consistent choices whereas a low threshold will lead to fast and inconsistent choices (Clithero, 2018). If one's ability to process information is limited and is experienced as effortful (i.e., draws upon cognitive resources), then these models provide an explanation for how investing effort in deliberation could help overcome initial biases and lead to greater EV maximizing choice. However, while these effort reduction models of choice can help explain the effects of deliberation on choice, they do not explain how one decides *a priori* how much effort to invest (i.e., where to set the decision threshold).

To address this gap, recent work has attempted to bridge the cognitive control literature and value-based decision-making literature by suggesting that control processes are used to adjust both attention and decision strategies use (Frömer & Shenhav, 2021). In turn, the choice of engaging in effortful control is governed by a cost-benefit trade-off (Shenhav et al., 2013, 2016, 2017; Silvetti et al., 2018) where the potential to obtain rewards is traded-off with the rewards forgone through inaction (Kurzban et al., 2013; Otto & Daw, 2019; Tajima et al., 2016). Similarly, other cost-benefit models posit a confidence-effort trade-off whereby the decision to expend effort is governed by the potential to increase feelings of subjective confidence when there is uncertainty about the preferred option or imprecise estimates of options' values (Lee &

Daunizeau, 2021). However, one critical limitation of this research is operationalizing cognitive effort in value-based choice. Thus, the goal of my thesis is to bridge cognitive control and value-based decision-making and understand the regulation of effort invested in a value-based choice by accounting for the underlying strategies decision-makers employ.

Section 1.1: How Do We Measure Momentary Changes in Effort Exertion?

One limitation to studying cognitive effort in both value-based decisions and cognitive control is establishing an *online* measure of effort exertion. Previously, both explicit choices (e.g., avoidance) and metacognitive (e.g., demand ratings) measures of effort have been used to measure cognitive effort. However, these measures do not reflect the momentary investment of effort itself but rather the post-hoc evaluation of effort after exertion. Other work has used behavioural performance (i.e., accuracy or response times) as a proxy for effort investment, however, task performance and effort outlay may not always share a monotonic relationship—effort is sometimes invested only when it is associated with performance increases (Otto et al., 2021). Thus, it is difficult to infer effort exertion from performance alone: responding more quickly could equally reflect random responding or the efficient use of attentional control. More recently, there has been an interest in establishing a physiological measure of momentary effort outlay.

One promising online measure of effort is task-evoked pupillary responses (TEPRs), which might serve as a viable index of cognitive effort exertion across a variety of task domains (Beatty, 1982). Across a diverse range of task domains, increasing the effort required to produce a correct response evokes larger TEPRs (van der Wel & Steenbergen, 2018). Specifically, TEPRs appear to track increases in working memory load (Heitz, Schrock, Payne, & Engle, 2008; Hopstaken, Van Der Linden, Bakker, & Kompier, 2015; Kahneman & Beatty, 1966), response inhibition requirements (Laeng, Ørbo, Holmlund, & Miozzo, 2011; Rondeel, Van Steenbergen, Holland, & van Knippenberg, 2015; van Steenbergen & Band, 2013), changes in task sets (Rondeel et al., 2015), syntactic complexity of written sentences (Just & Carpenter, 1993), and the difficulty of arithmetic (Ahern & Beatty, 1979; Steinhauer, Siegle, Condray, & Pless, 2004) and geometric analogy problems (Van Der Meer et al., 2010). However, it is unclear if pupil diameter actually indexes effort exertion or merely reflects task demand as both constructs are, by nature, tightly intertwined in many cognitive tasks (van der Wel & van Steenbergen, 2018). Put another way, when the level of task demand increases, successful task performance often requires more effort on the part of participants to meet this increased demand.

Indeed, disambiguating the effort and demand accounts of TEPRs is important because this body of extant pupillometry work, taken as a whole, finds inconsistent relationships between individual differences in cognitive task performance and TEPRs (van der Wel & van Steenbergen, 2018). For example, lending support to an effort account of TEPRs, heightened TEPRs were found to be associated with improved N-Back performance (Rondeel et al., 2015), and fewer errors on mental arithmetic problems (Ahern & Beatty, 1979). Other work has found that within-individual increases in TEPRs track improvements in performance on flanker-type tasks (Diede & Bugg, 2017). Interpreting these results within a cost-benefit framework, individuals with larger effort costs presumably invest less effort than individuals with smaller effort costs (Kool & Botvinick, 2018), and taking task performance as a proxy for effort investment, differences in effort investment would explain the finding that better performance in these tasks is associated with larger TEPRs. In support of this effort account, previous work has also demonstrated that individuals high in fluid intelligence (i.e. with low effort costs) exhibit better performance (i.e. more effort investment) and higher TEPRs on difficult geometric analogy problems (Van Der Meer et al., 2010).

At the same time, consistent with a demand view, larger TEPR differentiation between trial types in a Stroop task (i.e. congruent versus incongruent trials), was found to correlate with larger Stroop RT interference costs (i.e. worse performance; Laeng et al., 2011; Rondeel et al., 2015). This relationship between task performance and TEPRs might suggest that pupillary responses reflect the current level of task demand (i.e., the costs of cognitive control) rather than the actual effort exerted, as those with the worst performance also had the largest dilations. Further buttressing this view, a recent study observed a dissociation between physiological and performance measures, such that TEPRs reflect task conflict levels in a Stroop task (congruent versus neutral trials) in the absence of task conflict effects on performance (Hershman & Henik, 2019). That is, the observation that increases in task conflict level can drive increased TEPRs without a change in performance lends support to the demand hypothesis, as this account predicts that TEPRs should only differentiate to demand levels but not to invested effort. However, taking a cost-benefit view of effort investment, inter-individual differences in task performance could reflect variation in abilities (i.e., effort costs) and/or motivation (i.e., reward incentives). This might explain the variability in the reported relationships between task performance and physiology across these studies.

However, while there exists suggestive evidence that pupillary responses might index individual differences in effort outlay, it remains unclear if TEPRs also track within-individual reward-induced task performance improvements as a result of the decision to expend effort to obtain rewards. Indeed, examination of intra-individual differences are thought to be key in developing an understanding of TEPRs, as they can potentially circumvent issues associated with inter-individual comparisons (see van der Wel & van Steenbergen (2018) for an extended discussion). Taking a cost-benefit view of effort expenditure, we seek to disentangle the effort and demand accounts of pupil diameter by 1) modulating available rewards and 2) leveraging the inherent variability in individuals' cognitive control capacity.

Section 1.2: What makes a Value-Based Choice Effortful?

Exercising cognitive control by flexibly adapting responses to goals is thought to be effortful, but what makes value-based decision-making effortful is unclear. Yet, to establish an account of why we sometimes laboriously deliberate about choices and other times rely on heuristics necessitates an understanding of what makes a value-based choice difficult. In the previous section, we saw that the decision to exercise cognitive control—in this case to flexibly switch between task sets—follows a cost-benefit trade-off whereby the aversion to effort can be overcome by performance contingent rewards. Although value-based decisions are thought to rely on similar cognitive processes to cognitive control, there exists comparatively less compelling evidence that value-based decisions are experienced as effortful. In large part, the difficulty in defining the demand of a choice is understanding the underlying decision process.

Given two choice sets, how do we know which one is more demanding? Over the years, there have been several varied ways experimenters have manipulated the demand of choices—either by manipulating features of the environment or features of the choice set itself. In terms of environmental manipulations, a large focus has been on limiting the ability to execute time-consuming effortful deliberation either via manipulations of time pressure (Guo et al., 2017; Hu et al., 2015; Madan et al., 2015; Olschewski & Rieskamp, 2021; Zur & Breznitz, 1981) or taxing cognitive load (Hinson et al., 2003, 2019; Whitney et al., 2008). However, with these manipulations, participants are assumed to engage in effortful deliberation when they are not under constraints. In terms of manipulating choice features, previous work has focused on manipulating either the discriminability of or the amount of information. Aligned with the EV maximizing view of choice, others have used the similarity in (expected) value between options (i.e., discriminability) as a manipulation of demand (Lebreton et al., 2009; Lee & Daunizeau, 2021). However, two equally valued options could either vary in terms of their similarity of attributes. For example, two television shows could be equally liked, one being more educational and the other being more entertaining. Aligned with information-processing approaches to decision-making which assume that effort scales positively with the amount of information to be processed, researchers have either increased the number of options (Iyengar & Lepper, 2000) or the complexity of the options (Bernheim & Sprenger, 2020; Huck & Weizsäcker, 1999; Sonsino et al., 2002; Zilker et al., 2020). Thus, the greater number of attributes to consider when deciding, the more difficult the decision. However, these approaches to defining the demand of a choice *a priori* a largely agnostic to the degree of cognitive control the assumed heuristic requires. Yet, it remains equally unclear what makes one decision strategy more demanding than the other.

The value-based decision-making literature has used varied approaches to operationalizing cognitive effort of a heuristic, often producing contradictory interpretations. The effort reduction approaches to value-based choices, like Dual process theories and Information processing approaches, assume that effort is what is being conserved when fast responses are executed. This assumption follows from work on process tracing techniques in decision-making which defined the effort required to execute a given decision process as the number of Elementary Information Processes (EIP) (Johnson & Payne, 1985; Payne et al., 1993) needed to choose. For example, putting an attribute value in working memory, summing an option’s attribute values, or contrasting options by subtracting summed attribute values. However, it is particularly difficult to determine the effort required to implement a heuristic from first principles, as parsing information into discrete units may be arbitrary and depend on the level of granularity (Thomson & Oppenheimer, 2021). Furthermore, the EIP approach fails to account for the cognitive processes (e.g., cognitive control, working memory, attention) needed to implement heuristics which may depend on situational factors. For example, Bobadilla-Suarez & Love, 2018 found that, while the Take-The-Best heuristic is more frugal in terms of information use, it takes longer to implement and fares worse under time pressure than Tallying. However, which decision strategy is more effortful also depends on how the information (i.e., options' attributes) are presented. Thus, it is difficult to predict the demand of a heuristic for a given choice set and context.

One key component of cognitive control is the selection of relevant responses and inhibition of prepotent but inappropriate responses. Previous work has used *Strategic control*—the conflict between different decision strategies—to test how this control affects neural activity (Venkatraman et al., 2009). Here, I propose using Strategic control as a manipulation of task demands in value-based decisions-making: high control choices require selecting among strategies which prescribe different responses, while low control choices require selecting among strategies which prescribe the same choice. Using this operationalization, choice demands can vary independently of the heuristic chosen. Thus, choices, where the use of different heuristics would lead to disparate choices, should require greater cognitive control to select an option and be experienced as effortful.

Beyond the control demands of a choice, the effort deployed for deliberation should also vary as a function of the available rewards (da Silva Castanheira, LoParco, et al., 2021; Sandra &

Otto, 2018; Shenhav et al., 2013). In value-based choices, this would suggest that choices where there are high stakes and decision-makers stand to benefit more from choice (i.e., high average outcomes) should engender greater effort investment. However, previous work on value-based choice has found overall rewards on offer lead to response speeding which has been interpreted as evidence of effort disengagement (Frömer et al., 2019; Pirrone et al., 2018). This pattern of response speeding is also consistent with an effort investment account, as response speeding has previously been used as a marker of deploying cognitive control (da Silva Castanheira, LoParco, et al., 2021; Sandra & Otto, 2018). Thus, to disambiguate these accounts, I will use subjective reports to test whether response speeding when the reward on offer is high, reflect effort investment or disengagement.

Section 1.3: Are Demanding Value-Based Choices Avoided?

As discussed in the two preceding Sections, the decision to expend effort depends on the trade-off between a task's associated costs and benefits. But what happens when tasks have equated or no available rewards? Cost-benefit models of effort allocation predict that effort should be avoided when all else is equal—this prediction was outlined in Hull's (1943) law of least work. Yet, the data supporting cognitive effort avoidance pertains entirely to the deployment of cognitive control (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010; McGuire & Botvinick, 2010; Vogel et al., 2020; Westbrook & Braver, 2015) despite this principle often serving as a foundational assumption in the value-based decision-making literature (see Anderson, 2003 for a review).

Aligned with the law of least work, the literature on value-based choice has developed in large part on the assumption of effort minimization: decision-makers will employ strategies to reduce the cognitive demands of choice. Indeed, it is reasonable to assume that, much like cognitive control, the deployment of resources to implement decision strategies would be avoided in value-based choice as they rely on the same cognitive resources (Hinson et al., 2019; Whitney et al., 2008). Yet most of the evidence we have for this effort minimization principle in value-based choice has been indirect. This view is mainly supported by the heuristics and biases literature, which suggests that people avoid difficult deliberation by employing simplifying decision strategies (Gigerenzer & Selten, 2002; Goldstein & Gigerenzer, 2002; Payne et al., 1993). For example, people will often prefer no change or default options (Inman & Zeelenberg, 2002; Samuelson & Zeckhauser, 1988; Tsiros & Mittal, 2000), no action (omission bias, Ritov & Baron, 1992; inaction inertia, Tykocinski et al., 1995), and delay (choice deferral, Dhar, 1996). Additionally, features of the choice can also influence preferences: people avoid complex options (Zilker et al., 2020) or even avoid selecting altogether when there is too many options (Iyengar & Lepper, 2000). While there exists some debate as to whether the use of these heuristics reflects innate limitations of human cognition (Simon, 1957) or the rational use of limited resources (Gigerenzer & Selten, 2002; Goldstein & Gigerenzer, 2002), it is assumed that the use of these strategies is more frugal in terms of time and resources. However as reviewed in the previous section, there is some evidence that these strategies are not always faster or more frugal. While heuristics require less information, they also may require more attentional control needed to execute these heuristics (Bobadilla-Suarez & Love, 2018). Thus, it remains unclear whether the use of heuristics truly reflects the optimization of effort costs or some other quantity (e.g., feelings of confidence).

Section 1.4: Does Effort Exertion Predict Demand Avoidance?

The literature reviewed in two former sections suggests that we may engage in effort when there are high rewards at stake else, we may avoid effort when all else is equal. We also saw how these conclusions are based on indirect measures of effort (metacognition) or the choice and evaluation of demand. This means that we may not be able to disambiguate an effort account from other possible explanations. For example, in Section 1.2 we discussed how a cost-benefit account of effort in value-based choice predicts a larger effort investment as a function of increasing rewards on offer. An alternative account of response speeding in decision-making engendered by larger rewards suggests this pattern reflects disengagement of effort to resolve deadlocks and maximize long-term rewards (Pirrone et al., 2018), with some notable exceptions (see Frömer et al., 2019). And in Section 1.3 we discussed how cost-benefit account of effort in value-based choice predicts the avoidance of effort all else being equal, however, there is some work suggesting this may alternatively reflect maximizing one's subjective feelings of confidence (Lee & Daunizeau, 2021). Together, these gaps highlight the importance of an online measure effort exertion as discussed in Section 1.1.

Using pupil diameter as an online measure of effort during value-based choices would help disambiguate the above-described ambiguities. For Example, if pupils dilate more when the rewards at stake are higher for the demanding choices, this suggests that the response speeding typically observed does in fact reflect reward-induced effort investment. Additionally, pupil diameter during difficult choices—an index of momentary effort investment—should correlate with demand avoidance if these choices reflect the aversiveness of effort exertion. Yet, most of the work on effort and pupillometry has largely focused on cognitive control with little work investigating the relationship in value-based decisions. While there is some evidence that pupillary responses may track effort investment in value-based decisions (Eldar et al., 2021), there is other evidence suggesting pupil dilations may reflect reward on offer (Bray et al., 2008; J. P. O'Doherty et al., 2003), risk (Lavín et al., 2014), or even surprising outcomes (Preuschoff et al., 2011; Van Slooten et al., 2018)—making it difficult to infer effort investment from increases in pupil diameter. Thus, it is possible that pupil diameter could help corroborate whether task behaviour reflects cost-benefit trade-offs; but it is first necessary to show that pupil diameter during value-based choice tracks demand levels in value-based choices.

Section 1.5: Summary & Specific Aims

In my thesis, I will elucidate the relationship between effort and decision-making and unify the predictions of Cost-Benefit models across disparate domains of behaviour: cognitive control and value-based choice. Below, I propose several experiments to corroborate the subjective, behavioural, and physiological experience of effort exertion across domains. The goals of my thesis are fourfold:

1) In Section 2, I will arbitrate between the effort and demand accounts of pupil diameter by leveraging Cost-Benefit models of effort exertion and assess whether task-evoked pupillary responses index both within-individual reward-induced modulations of effort investment and between-individual differences in cognitive control.
2) In Section 4, I will probe subjective feelings of demand in value-based choices to understand whether strategic conflict between heuristics and low discriminability in EV differences engenders greater feelings of demand.
3) In Section 4, I will use the stimuli rated as demanding in Section 3 to test whether demanding value-based choices are avoided all else being equal as posited by Cost-Benefit models of effort.

4) In Section 4, I will test whether pupil diameter during value-based choice tracks both within-individual changes in decision demands and between-individual differences in decision avoidance.

Together, the results of our experiments will integrate our understanding of effort across domains of behaviour and test the predictions of Cost-Benefit models as a possible unifying framework.

Section 2: Pupil Diameter as a Measure of Online Effort Exertion

Section 2.1: Introduction

Why do we, under some circumstances, rely on costly, effortful cognitive processing, while other times turn to relatively effortless, cognitively ‘inexpensive’ forms of processing? A spate of recent research has endeavored to examine the situational and individual factors which govern the deployment of cognitive effort in service of task goals . Of particular interest in this burgeoning cognitive effort literature are tasks requiring cognitive control—broadly defined as the capacity to flexibly adapt one’s behavior and appropriately direct cognitive processing in accordance with internally maintained goals. Cognitive control is readily measurable in the lab using, for example, interference tasks such as the Stroop or flanker (Botvinick et al., 2001). In these tasks, successful performance is thought to reflect not only an individual’s cognitive capacity (i.e., executive function ability) but also the individual’s decision to invest cognitive effort at that particular moment. According to one influential account, this decision to engage in (or withhold) cognitively effortful processing is governed by the inherent trade-off between the costs of exerting effort and the benefits (i.e., rewards) potentially conferred by effort exertion (Shenhav et al., 2013). On this view, previous work has found monetary incentives to improve task performance by offsetting the costs of cognitive resource allocation, reflecting the mobilization of effort (Capa et al., 2013; Chiew & Braver, 2014; Hübner & Schlösser, 2010;

Otto & Daw, 2019; Padmala & Pessoa, 2011; Sandra & Otto, 2018). Furthermore, it has been shown that people consistently avoid expending cognitive effort when rewards are held constant (Inzlicht et al., 2014; Westbrook & Braver, 2015), and this avoidance appears more prevalent in individuals with limited cognitive capacity which, in turn are presumed to have higher effort costs (Kool et al., 2010). A key challenge in developing an account of the regulation of effortful behavior (or 'metacontrol') is the specification of a trial-by-trial measurement of an individual's momentary cognitive effort outlay—that is, quantifying the amount of effort an individual exerts—in accordance with costs and benefits. One potentially promising online effort measure is pupil diameter. Indeed, a considerable body of psychophysiological work suggests that task-evoked pupillary responses (TEPRs) might serve as a viable index of cognitive effort exertion (Beatty, 1982), finding that across a diverse range of task domains, increasing the effort required to produce a correct response evokes larger TEPRs (van der Wel & van Steenbergen, 2018). Specifically, TEPRs appear to track increases in working memory load (Heitz et al., 2008; Hopstaken et al., 2015; Kahneman & Beatty, 1966), response inhibition requirements (Laeng et al., 2011; Rondeel et al., 2015; Van Steenbergen & Band, 2013), changes in task sets (Rondeel et al., 2015), syntactic complexity of written sentences (Just & Carpenter, 1993), and the difficulty of arithmetic (Ahern & Beatty, 1979; Steinhauer et al., 2004) and geometric analogy problems (Van Der Meer et al., 2010). However, it is unclear if pupil diameter actually indexes effort exertion or merely reflects task demands as both constructs are, by nature, tightly intertwined in many cognitive tasks (van der Wel & van Steenbergen, 2018). Put another way, when the level of task demand increases, successful performance often requires more effort on the part of participants to meet this increased demand. To demonstrate pupil diameter might serve as a viable measure of cognitive effort outlay, separate from task demand, the present study seeks to examine whether changes in TEPRs indeed reflect levels of effort investment—both varying intrinsically as a function of individual differences, and extrinsically, evoked by changes in reward incentives—while holding task demands constant. Indeed, disambiguating the effort and demand accounts of TEPRs is important because this body of extant pupillometry work, taken as a whole, finds inconsistent relationships between individual differences in cognitive task performance and TEPRs (van der Wel & van Steenbergen, 2018). For example, lending support to an effort account of TEPRs, heightened TEPRs were found to be associated with improved Nback performance (Rondeel et al., 2015), and fewer errors on mental arithmetic problems (Ahern & Beatty, 1979). Other work has found that within-individual increases in TEPRs track improvements in performance on flanker-type tasks (Diede & Bugg, 2017). Interpreting these results within a cost-benefit framework, individuals with larger effort costs presumably invest less effort than individuals with smaller effort costs (Kool & Botvinick, 2018), and taking task performance as a proxy for effort investment, differences in effort investment would explain the finding that better performance in these tasks is associated with larger TEPRs. In support of this effort account, previous work has also demonstrated that individuals high in fluid intelligence (i.e., with low effort costs) exhibit better performance (i.e., more effort investment) and higher TEPRs on difficult geometric analogy problems (Van Der Meer et al., 2010). At the same time, consistent with a demand view, larger TEPR differences between trial types in a Stroop task (i.e., congruent vs. incongruent trials), were found to correlate with larger Stroop RT interference costs (i.e., worse performance; Laeng et al., 2011; Rondeel et al., 2015). This particular relationship between task performance and TEPRs might suggest that pupillary responses reflect the current level of task demand (i.e., the costs of cognitive control) rather than the actual effort exerted, as those with the worst performance also had the largest dilations. Further buttressing this view, a recent study observed a dissociation between physiological and performance measures, such that TEPRs reflect task conflict levels in a Stroop task (congruent vs. neutral trials) in the absence of task conflict effects on performance (Hershman & Henik, 2019). That is, the observation that increases in task conflict level can drive increased TEPRs without a change in performance lends support to the demand hypothesis, as this account predicts that TEPRs should only differentiate to demand levels, but not to invested effort. However, taking a cost-benefit view of effort investment, interindividual differences in task performance could reflect variation in abilities (i.e., effort costs) and/or motivation (i.e., reward incentives). This might explain the variability in the reported relationships between task performance and physiology across these studies. Furthermore, while there is suggestive evidence that pupillary responses might index individual differences in effort outlay, it also remains unclear if TEPRs also track within-individual reward-induced task performance improvements as a result of a decision to expend increased effort to obtain rewards. Indeed, examination of intraindividual differences are thought to be key in developing an understanding of TEPRs, as they can potentially circumvent issues associated with interindividual comparisons (see van der Wel & van Steenbergen, 2018, for extended discussion). Taking a cost-benefit view of effort expenditure, here we seek to disentangle the effort and demand accounts of pupil diameter by (1) modulating available rewards and (2) leveraging the inherent variability in individuals' in both cognitive capacity and intrinsic motivation to expend effort. In line with the cost-benefit view of effort, a large body of work demonstrates how reward incentives mobilize cognitive effort (Botvinick & Braver, 2015). As a consequence, task performance increases when large monetary rewards hinge on the successful deployment of cognitive control, compared with smaller reward incentives (Aarts et al., 2014; Bijleveld et al., 2009) or the absence of reward incentives altogether (Hübner &

Schlösser, 2010; Locke & Braver, 2008; Padmala & Pessoa, 2011). For example, in task-switching paradigms—where task switch costs are thought to reflect, in part, reconfiguration costs necessary for shifting between task sets (Monsell, 2003)—larger performance-contingent monetary rewards engender task switch costs reductions, which are interpreted as a marker of increased effort investment (Capa et al., 2013; Fröber & Dreisbach, 2016; Kleinsorge & Rinkenauer, 2012; Otto & Vassena, 2021). If pupil diameter is thought to reflect effort investment, we would also expect that reward-induced changes in task performance should also be reflected in TEPRs. Indeed, previous pupillometry work finds that reward incentive levels increase TEPRs on difficult trials in a working memory task (Bijleveld et al., 2009). Similarly, other work has also found reward induced increases in both transient (i.e., trial-by-trial) and sustained pupil diameter, suggesting a distinct role for using pupil diameter to track changes in motivational state (Chiew & Braver, 2013, 2014). However, while these studies find that reward manipulations effectively modulate TEPRs, they did not examine whether these TEPR modulations are related to reward-induced task performance, which would lend strong support to an effort view of TEPRs (van der Wel & van Steenbergen, 2018). Thus, manipulating reward incentives offers an opportunity to study the intraindividual modulations of effort exertion (i.e., reward induced changes in task performance) and its subsequent effects on pupil diameter, while holding task demands (i.e., difficulty) constant. Finally, individual differences in cognitive capacity (i.e., effort costs) might bear upon the relationship between TEPRs and behavioral markers of effort exertion, as effort avoidance is observed to be more prevalent in individuals with limited cognitive ability (Kool et al., 2010), and more recent work finds that individuals with lower executive function (EF) capacity benefit the most from monetary incentives during task-switching (Sandra & Otto, 2018). Thus, we also assessed how differences in more general

EF capacity, as measured by Stroop interference costs—which are thought to tap into EF abilities (Kane & Engle, 2003)—moderate the relationship between rewards and effort allocation. While the Stroop task and task-switching rely, in part, on shared EF capacities (Miyake et al., 2000), they also impose unique requirements, respectively, on inhibition and set-shifting processes. Our use of qualitatively different EF-dependent tasks to separately assess individual differences underscores the generalizability of the relationship between effort costs and effort expenditure, as evidenced behaviorally and in TEPRs, while at the same time mitigating circularity issues potentially arising from the use of a task-switch-based measure to understand the relationship between task switch costs and TEPRs. Beyond cognitive capacity, other work has highlighted the variability in people's aversion to exerting effort, suggesting that some individuals value effortful thought more than others (Inzlicht et al., 2018), over and above differences cognitive ability. Indeed, differences in intrinsic effort valuation predict the amount of money a person is willing to accept to exert effort (Westbrook et al., 2013) and the extent of reward-induced improvements on task performance (Sandra & Otto, 2018). Therefore, we further assess how interindividual differences in effort avoidance, operationalized by the Need for Cognition scale (NFC; Cacioppo et al., 1984), predict reward-induced effort recruitment, both behaviorally and physiologically. Finally, we examine how tonic (i.e., nonstimulus-evoked) changes in pupil diameter relate to task engagement and arousal. Previously, tonic pupil dilations have been shown to reflect control state changes (i.e., task engagement; (Gilzenrat et al., 2010), reward-induced changes in arousal (Chiew & Braver, 2013, 2014), and individual differences in cognitive ability (Heitz et al., 2008; Van Der Meer et al., 2010). Accordingly, we also examine the extent to which reward incentives increase tonic pupil diameter, and whether those high in EF capacity (as indexed by Stroop interference costs) also have larger tonic pupil diameter, as was previously reported for those high in fluid intelligence (Van Der Meer et al., 2010) and working memory (Heitz et al., 2008). Finally, we examine whether individual differences in motivation to deploy effort (indexed by NFC) relate to tonic pupil diameter, and whether the effect of reward on tonic pupil diameter depends on these individual differences.

Section 2.2: Methods

Overall experimental procedure

We first assessed individual differences in motivation to exert effort (NFC) and EF abilities (Stroop interference costs). Following the individual difference assessments, participants were asked to complete a 'baseline' tasks witching paradigm in the absence ***of*** reward incentives, before completing the same paradigm under two different levels of reward incentives, termed low-reward and high-reward blocks. We recorded pupil diameter during all task-switching blocks.

Participants

Eighty English-speaking participants (55 females; mean age = 22.08 years, SD = 3.03 years) were recruited from the McGill University community for a base remuneration of $20 CAN and a performance-contingent cash bonus of up to $13.20. All participants had corrected-to-normal vision, and had no reported colour blindness or diagnosis of psychiatric or neurological conditions. Prior to the experiment, participants provided informed consent in accordance with the McGill University Research Ethics Board. We excluded the data of five participants missing more than 20 trials, one participant who failed to perform the task with at least 80% accuracy overall, and four participants for which no reliable pupil dilation data could be collected due to technical issues with the eye tracker. For those analyses involving the NFC, we excluded two additional participants who were missing NFC questionnaire responses. Finally, for those analysis involving the Stroop task, we excluded an additional six participants.

Materials and Procedure

Prior to completing computerized tasks, participants first completed the Need for Cognition (NFC) questionnaire to assess individual differences in their tendency to engage in effortful thinking (Cacioppo et al., 1984). The questionnaire involves rating 18 statements—such as "I find satisfaction in deliberating for hard and long for hours" and "I only think as hard as I have to"—rated on a scale of how characteristic they are of the participant (1 = extremely uncharacteristic to 5 = extremely characteristic). Participants also completed the behavioral approach/inhibition scales (BIS/BAS; (Carver & White, 1994), which was not examined in the present analysis. In the computerized task portion of the experiment, participants were seated comfortably in front of a 24-inch monitor set to a resolution of 1,280 × 1,024 pixels in a dimly lit room. Participants were instructed to keep their heads still and rested on a mount positioned 60 centimeters away from the screen. During both the Stroop and switching paradigm tasks, participants' right pupil diameter was measured using an EyeLink 1000 eye tracker (SR Research, Osgoode, ON) set to a sampling rate of 250 Hz. Stimuli were presented using PsychoPy (Version 1.85.3), synchronized with the eye tracker. Prior to each task block, participants underwent a standard 9-point calibration procedure.

Stroop interference task

Participants completed a computerized version of the Stroop interference paradigm (Kerns et al., 2004; Otto et al., 2015) to measure individual differences in executive function. Participants were instructed to identify, as quickly and accurately as possible, the color (i.e., green, red or blue) of the font a word was presented in (i.e., 'GREEN', 'RED', or 'BLUE'), corresponding to three keys (‘j’, ‘k’, or ‘l’), with stimulus–response mapping counterbalanced between participants. Participants completed a total of 120 trials, on 90 of which the word and font color matched (congruent trials), and on the remaining 30 trials they did not match (incongruent trials), presented in a pseudorandomized order. Before starting the task, participants were given 10 practice trials to get accustomed to the timing and response procedure and received trial-by-trial feedback (600 ms) as to whether their response was correct or incorrect. During the task, participants were shown a fixation cross in yellow for 1.5 seconds before being shown the target and given 1.5 seconds to respond without feedback.

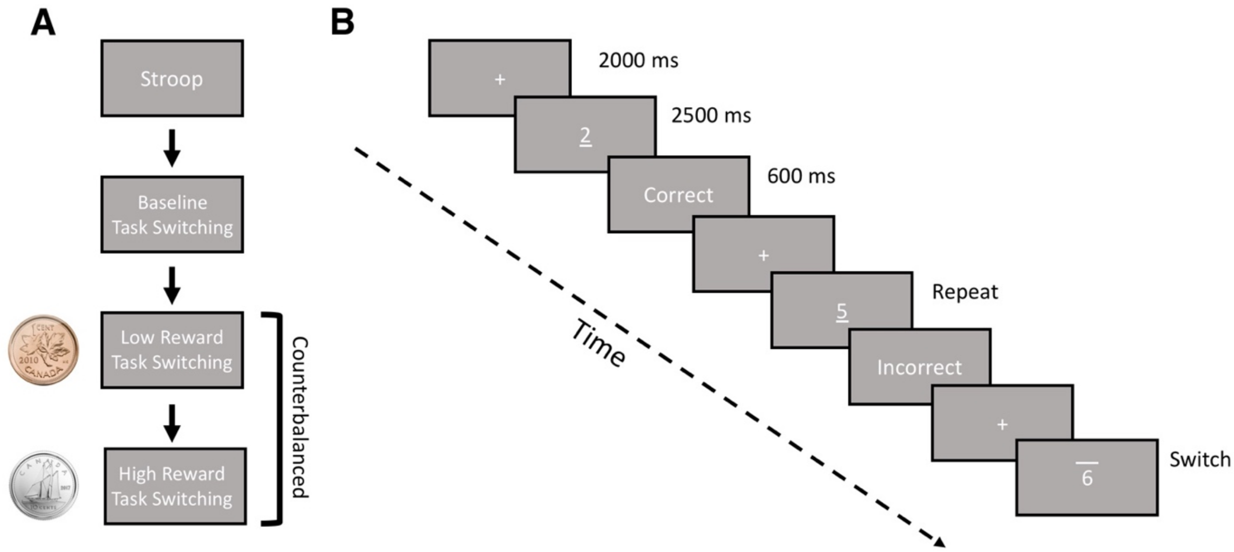
Task-switching paradigm

After completing the Stroop task, participants completed a number magnitude-parity task-switching paradigm (Kool et al., 2010). In this task, participants were presented a single digit (9, 8, 7, 6, 4, 3, 2, or 1) and were asked to judge either the magnitude (larger or smaller than 5) or the parity (even or odd) of the number, depending on the position of a bar above or below the digit, with position-task mappings counterbalanced between participants. The task (i.e., magnitude or parity) cue was chosen to reduce luminance-driven changes in pupillometric responses. Importantly, for approximately half of the trials, participants repeated the same task from the previous trial and on the other half of trials switched to the other task. The order of presentation of repeat and switch trials was pseudorandomized. Additionally, participants were presented with 10 practice trials with accuracy feedback to adjust to the timing and response procedure. On each trial, a fixation cross was presented in yellow for 2 seconds before being presented with the target digit, and participants were given 2.5 seconds to respond, followed by the same accuracy feedback immediately after participants’ responses (Chiew & Braver, 2013; Heitz et al., 2008; Hershman & Henik, 2019; Rondeel et al., 2015). The task was broken up into

6 blocks, each consisting of 60 trials. For the first two blocks, participants did not receive any reward incentives for correct responses. For the subsequent four reward blocks (see Fig. 1), participants were informed that they would receive either 10 cents (i.e., high reward) or 1 cent (i.e., low reward) per correct response. The reward manipulation was further made apparent by a change to task feedback from baseline signaling the amount of money earned on the trial (i.e., "+10 cents" or "+1 cent"; "+0 cents" for correct and incorrect responses, respectively). The order of reward block presentation was also counterbalanced between participants, such that Blocks 3–4 were associated with high reward, and Blocks 5–6 were associated with low reward, or vice versa. Experimental blocks were separated by a participant-paced break to minimize fatigue (see Fig. 1).

Figure 1.

A. Schematic of the phases of the experiment participants experienced. **B.** Illustration of the timeline of the task-switching paradigm where subtasks (i.e., magnitude or parity judgement) were cued by a bar presented either above or below the digit (with task-cue pairings counterbalanced between participants).



Behavioral Data Analysis

We analyzed participants' responses on both the Stroop and task-switching tasks using linear mixed-effects regressions, using the lme4 package (Version 1.1.14; Bates & Maechler, 2019) for the R programming language. For both tasks, we removed the first 10 trials of the experiment to mitigate the influence of task novelty and/or early learning trials upon TEPRs, as well as trials in which participants failed to respond within the response window (2% of total trials for the Stroop, and <1% for task-switching). Both Stroop interference effects and task switch costs were calculated using RTs for correct trials only, which were log-transformed to remove skew (Ratcliff, 1993). We also removed unexpectedly fast or slow trials which were greater than or less than three standard deviations from the participant mean (Jiang et al., 2015; Laeng et al., 2011; Padmala & Pessoa, 2011; Qiao et al., 2017), resulting in the removal of less than 1% of trials (for each trial type). Each individual participant's Stroop interference effect was calculated as the estimated per-subject regression coefficient representing the effect of trial incongruence. For all RT regressions, we included a linear predictor of trial block to account for practice effects, and categorical nuisance variables accounting for the previous trial type (i.e., incongruent/congruent or switch/repeat), previous errors, and key repetitions with respect to the previous trial. Finally, in the task-switching regressions, we included a response congruence predictor, specifying whether the correct response for a given stimulus mapped to the same or different keys for both tasks.

Pupillary Data Analysis

Pupillary data were preprocessed in MATLAB (Version 2017b) before calculating a trial-by-trial task-evoked pupillary response (TEPR). First, eye blinks were detected and corrected using linear interpolation, and pupil diameter measurements were passed through a high-pass Butterworth filter to remove slow drift below a frequency of 4Hz, following Nasser et al (2012). After this pre-processing step, pupil diameter was first Z-scored within-block in order to make pupil units comparable between blocks (de Gee et al., 2014; Nassar et al., 2012; Urai et al., 2017), and then baseline-corrected on a trial-by-trial basis by subtracting the mean diameter of a 200ms baseline period prior to stimulus presentation, following previous work (Eckstein et al., 2019; Hershman & Henik, 2019). TEPRs were subsequently calculated as the maximum pupil diameter (Gilzenrat et al., 2010) observed between 1000ms and 3000ms after stimulus onset—a time window which has been previously shown to contain the pupillary response of interest in similar tasks (Laeng et al., 2011; Rondeel et al., 2015; see Figure 2). Critically, the calculation of TEPRs did not depend on participants' response latency, as switch and repeat trials typically engender different RTs. Trial-by-trial tonic pupil diameter was calculated as the average unfiltered pupil diameter during the 200ms baseline period before stimulus onset, following Chiew and Braver (2013). We also used mixed-effects regressions to examine task-switching effects upon TEPRs, predicting trial-by-trial TEPRs, as computed above, on the basis of trial type (i.e. Repeat or Switch) and subtask (i.e. Magnitude vs Parity).

To examine how TEPRs related to individual differences in task performance in Baseline blocks, we calculated switch costs (switch trial RTs minus repeat trials RTs) for each 30-trial 'mini-block' (yielding two switch costs per experimental block). Afterward, we estimated a mixed-effects regression predicting these RT switch costs estimates as a function of mean mini-block TEPRs on switch trials, mini-block number (to account for practice effects), as well as each participant's Stroop interference cost and NFC scores (z-scored across participants), with random effects taken over intercepts and mini-block. To test whether individual differences in reward-induced TEPR changes tracked switch cost reductions, we computed reward-induced RT switch cost changes by subtracting baseline switch costs from the mean RT switch cost across both Reward blocks and the analogous per-participant change in switch trial TEPRs (Reward - Baseline). We then estimated a linear regression predicting change in RT switch costs based on change in TEPRs, Stroop costs, NFC scores (z-scored across participants) and a categorical regressor of reward presentation order.

Section 2.3 Results

Task Performance

As typically observed in the Stroop task, participants were slower ($\boldsymbol{\beta}$ = 0.2578, SE = 0.0115, p <.0001; see Fig. 2b and Supplemental Table S1) and less accurate ($\boldsymbol{\beta}$ = -1.7928, SE = 0.1803, p < .0001; see Supplemental Table S2) to respond to incongruent trials compared to congruent trials. From these RTs, we calculated Stroop interference costs as the estimate of the per-participant incongruent effect, yielding our individual difference measure of executive function (EF). Analyzing performance on the Baseline task-switching paradigm (without rewards), we observe the typical task switch costs (Monsell, 2003): participants were both slower ($\boldsymbol{\beta}$ = 0.1431, SE = 0.0087, p < .001; see Table 2) and less accurate ($\boldsymbol{\beta}$ = -0.4508, SE = 0.0937, p < 0.001; see Supplemental Table S5) on task switches compared to task repetitions (see Table 1).

Figure 2.

A. Time Series depicting the stimulus-onset (dashed line) locked average pupil diameter over the course of trials. Median response times for each trial type are depicted as solid vertical lines. The shaded area shows the time period used to calculate TEPRs. **B.** Bar graph depicting the average TEPR by trial type (Switch vs Repeat) and Reward condition. Error bars represent bootstrapped 95% confidence intervals.

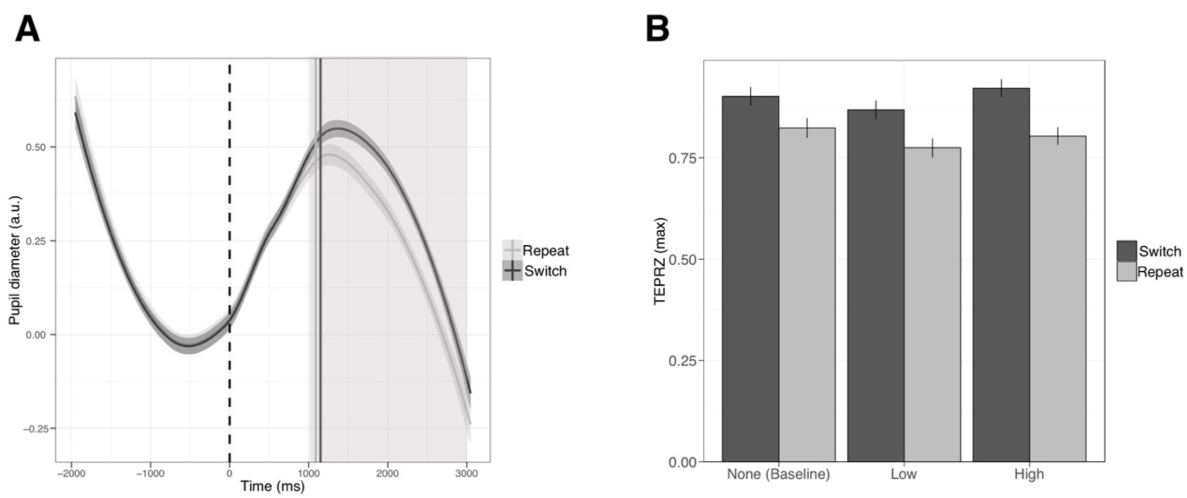


Table 1.

Average median RTs, TEPRs, and accuracy for congruent versus incongruent trials in the Stroop task and in repeat and switch trials across the three blocks of the task-switching paradigm.

	RT (ms)		***Accuracy***		***TEPR***	
	Mean	***SD***	***Mean***	***SD***	***Mean***	***SD***
Stroop task						
Congruent	*626.36*	*79.7*	*0.9865*	*0.0188*		
Incongruent	*831.35*	*151.87*	*0.9283*	*0.0741*		
Task switching (baseline)						
Task repeat	*1,010.95*	*151*	*0.9423*	*0.0565*	*0.7993*	*0.3778*
Task switch	*1,176.76*	*175.67*	*0.9132*	*0.0655*	*0.9004*	*0.4086*
Task switching (low reward)						
Task repeat	*960.45*	*163.41*	*0.9524*	*0.0421*	*0.7513*	*0.3544*
Task switch	*1,094.94*	*186.33*	*0.9356*	*0.0519*	*0.839*	*0.382*
Task switching (high reward)						
Task repeat	*949.97*	*156.17*	*0.9678*	*0.033*	*0.7933*	*0.3646*
Task switch	*1,078.30*	*167.74*	*0.9501*	*0.04941*	*0.915*	*0.3739*

Table 2.

Mixed-effects regression coefficients indicating the influence of trial type (task switch versus task repeat), reward level (reward vs. baseline), and the interaction between reward and trial type on RTs in the task-switching paradigm.

Predictors	**Estimates**	**SE**	**p**
(Intercept)	6.9823	0.0277	<.001*
Switch (vs. repeat)	0.1431	0.0087	<.001*
Reward (vs. none)	−0.0252	0.0107	.019*
Trial	−0.0002	0.0001	.001*
Task (parity vs. magnitude)	0.0245	0.0234	0.294
Prev. switch	0.0106	0.0019	<.001*
Prev. missed	0.0041	0.0183	0.823
Prev. incorrect	0.0145	0.0041	<.001*
Key repetition	−0.0231	0.0022	<.001*

Bar (above vs. below)	−0.0066	0.0234	0.779
Congruent	−0.0408	0.0105	<.001*
Switch (vs. Repeat) × Reward (vs. None)	−0.0237	0.0077	.002*

We also examined task-switching performance across High- and Low- reward conditions (Figure 2) but, mirroring past findings (Sandra & Otto, 2018), we did not observe a significant effect of reward effect upon switch costs (Task Switch x Reward interaction β = -0.0087, SE = 0.0083, p = .29, see Supplemental Table S3), suggesting either a weak effect of reward, large heterogeneity in individual response to reward, or both. Similarly, we did not observe a significant reward effect on switch costs expressed in terms of accuracy (Switch x Reward interaction; β = -0.1277, SE = 0.1503, p = .39; see Supplemental Table S4), but found a main effect of reward on accuracy such that participants were more accurate overall on High- versus Low- reward trials (β = 0.4613, SE = 0.1191, p < .001, see Supplemtnal Table S4). Collapsing across reward levels, we found that reward reduced both individuals' RTs (β = -0.0252, SE = 0.0107, p = .01, see Table 2), and switch costs expressed in RT when compared to Baseline blocks (β = -0.0237, SE = 0.0077, p = .002, see Table 2), as well as a main effect of reward on accuracy, such that rewarded responses were more accurate (β = 0.2863, SE = 0.0937, p = .03; see Supplemental Table S5), but failed to find this effect on switch costs expressed in terms of accuracy (i.e. Switch x Reward interaction; β = 0.0558, SE = 0.1194, p = .64; see Supplemental Table S5).

Task-Evoked Pupillary Responses (TEPRs)

Examining Task-Evoked Pupillary Responses (TEPRs) on correct trials, we observed a significant difference between switch trials in the baseline block in comparison to repeat trials (see Figure 2A), whereby switches engendered larger TEPRs than repetitions ($\boldsymbol{\beta}$ = 0.0881, SE =

0.0163, p < .001; see Table 3), thus supporting the demand account. As seen in Figure 2, TEPRs peaked in a window ranging from 1 to 2 seconds post-stimulus onset, where these switch-versus-repeat differences were observed. Comparing reward conditions to baseline, we found no effect of reward on TEPRs (***β*** = -0.0389, SE = 0.0333, p = .24; see Table 3), nor an interaction between reward condition and trial type (Reward x Switch; ***β*** = 0.0173, SE = 0.0187, p = .35; see Table 3 and Fig 3b), suggesting that reward did not increase TEPRs on average.

Figure 3.

Scatter plot depicting the relationship between TEPRs on switch trials (horizontal axis) and switch costs during the Baseline block (vertical axis).

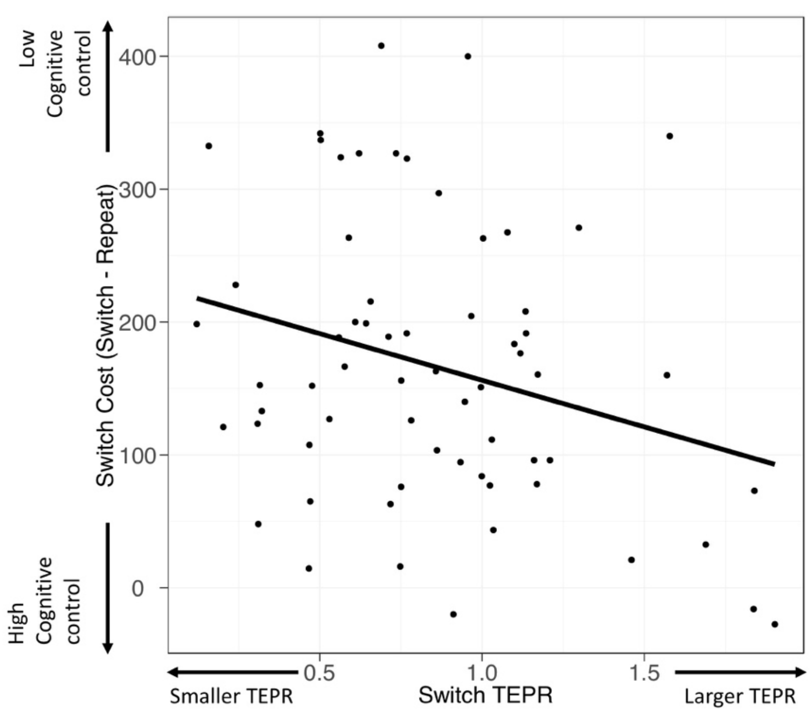


Table 3.

Mixed-effects regression coefficients indicating the influence of trial type (task switch versus task repeat), reward level (reward vs. baseline), and the interaction between reward and trial type on TEPRs in the task-switching paradigm.

Predictors	Estimates	*SE*	*p*
(Intercept)	0.5701	0.0618	<.001*
Switch (vs. repeat)	0.0881	0.0163	<.001*
Reward (vs. none)	−0.0389	0.0333	0.242
Trial	0.0341	0.0638	0.592
Task (parity vs. magnitude)	−0.0068	0.0043	0.113
Prev. switch	−0.1847	0.0503	<.001*
Prev. missed	−0.1000	0.0137	<.001*
Prev. incorrect	0.0001	0.0001	0.697
Key repetition	−0.0227	0.0043	<.001*
Bar (above vs. below)	−0.0321	0.0638	0.615
Congruent	−0.0262	0.0136	0.054
Switch (vs. Repeat) × Reward (vs. None)	0.0173	0.0187	0.355

Relationship Between TEPRs and Task Switch Costs at Baseline

To arbitrate between potential effort and demand accounts of pupillary responses, we first sought to test if larger TEPRs during task-switching would predict greater effort exertion in task switching, as measured by task switch costs—a result uniquely predicted by the effort account. As seen in Figure 3, we found a significant effect of switch trial TEPRs upon RT switch costs during the Baseline blocks, indicating that larger pupil dilations on switch trials predicted smaller switch costs at baseline ($\boldsymbol{\beta}$ = -25.6165, SE = 11.8921, p = .03; see Table 4).

Figure 4.

Scatter plot depicting the relationship between reward-induced changes in TEPRs on task switch trials, computed as the difference between rewarded and Baseline blocks (horizontal axis) and reward-induced change in RT switch costs, computed as the difference between rewarded and Baseline blocks (vertical axis).

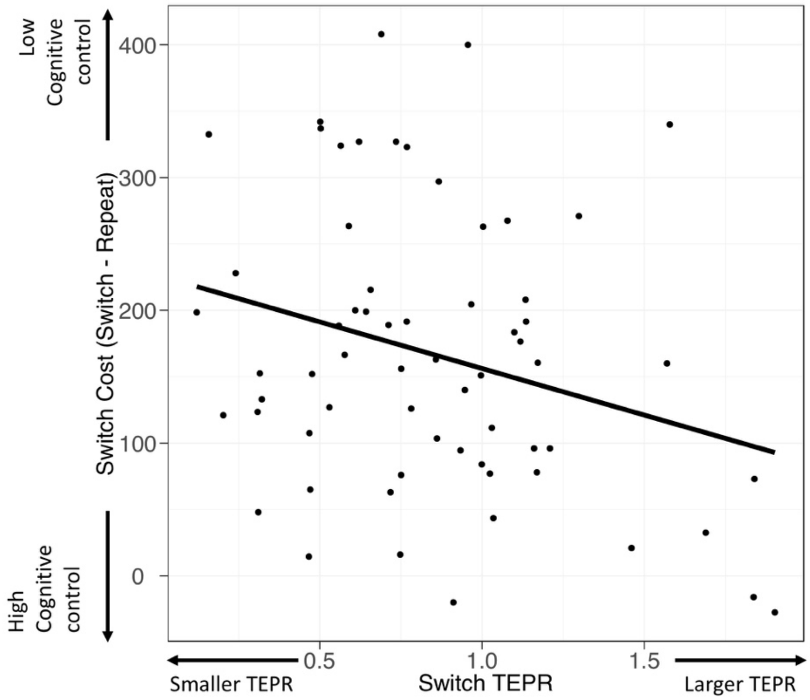


Table 4.

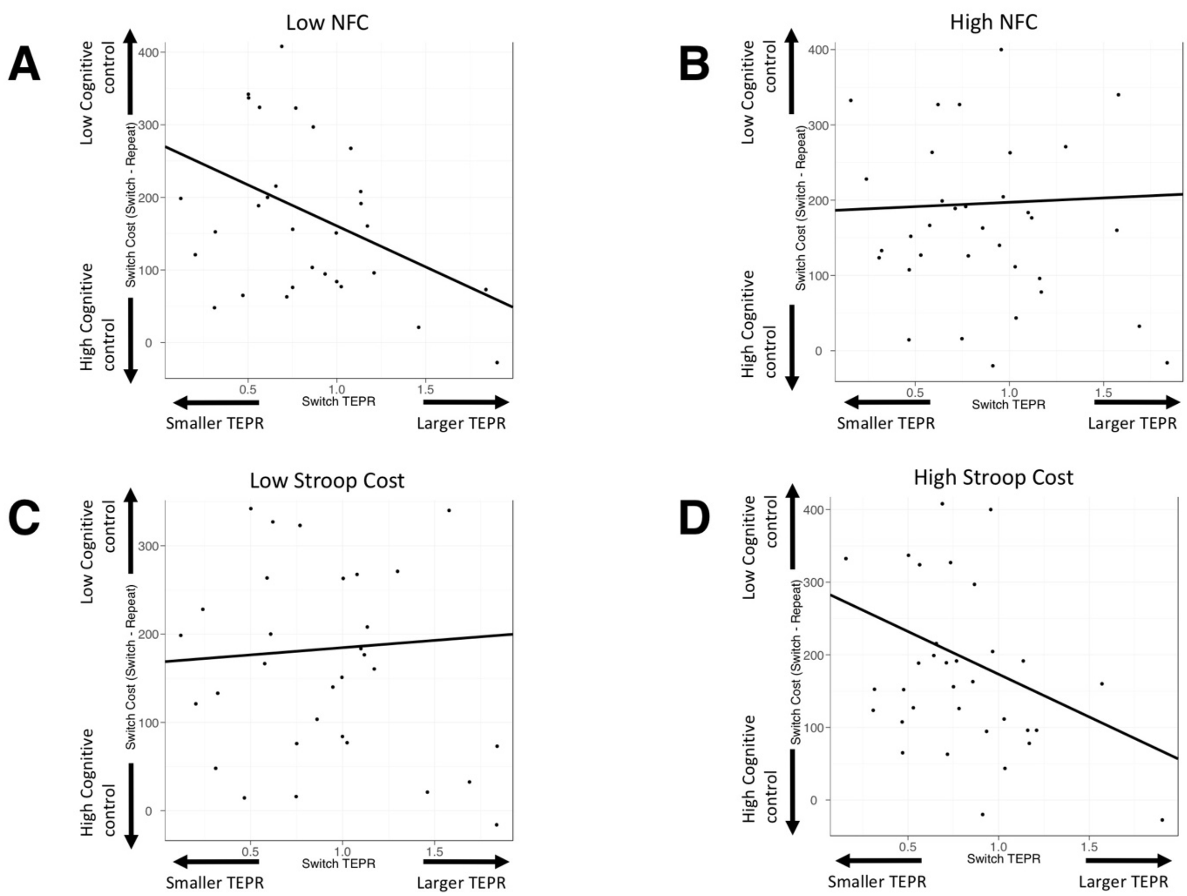
Mixed-effects regression coefficients indicating the influence of TEPRs, NFC scores, Stroop costs, and their interactions on mini block switch costs in the baseline block of the task-switching paradigm.

Predictors	Estimates	*SE*	*p*
(Intercept)		30.0812	<.001*
TEPR		11.8921	.031*
Stroop cost		11.7237	0.46
NFC		12.0031	0.435
Mini block		10.2607	0.371
TEPR × Stroop Cost		11.3658	.012*
TEPR × NFC		13.8212	0.056

We further probed whether individual differences in Stroop RT costs and NFC might bear upon the observed relationship between TEPRs and task switch costs at baseline. As seen in Fig. 5, both Stroop RT costs and NFC scores appeared to modulate the strength of the relationship between switch costs and TEPRs. Statistically, we found a significant interaction between TEPR and Stroop RT costs ($\beta = -28.6091$, $SE = 11.3658$, $p = .012$) while the interaction between TEPRs and NFC only reached marginal significance ($\beta = 26.37$, $SE = 13.8212$, $p = .056$; see Table 4). In other words, while TEPRs significantly predicted individual task switch costs at baseline across the entire sample, this relationship was stronger for individuals lower in EF ability as operationalized by Stroop RT costs, and marginally stronger for low-NFC individuals.

Figure 5.

Scatter plots depicting the relationship between TEPRs on switch trials (horizontal axes) and switch costs during the baseline block (vertical axes) as a function of individual differences. The first row (a and b) is a median split of participants based on Need for Cognition (NFC) scores, and the second row (c and d) groups participants based on a median split performed upon Stroop RT costs.



Importantly, EF ability and NFC were not able to predict task switch costs at baseline, as we found neither a significant main effect of Stroop RT costs (β = 8.6686, *SE* = 11.7237, *p* =.46; see Table 4) nor NFC scores (β = 9.3651, *SE* = 12.0031, *p* = .43; see Table 4). The absence of a relationship suggests that the moderating effect of individual difference measures on the relationship between TEPR and task performance is not driven by overall differences in performance. Furthermore, EF ability and NFC were not significantly correlated ($r = -.02$, $p = .88$), suggesting that these two measures tap into dissociable constructs. Finally, to control for the possibility that these individual differences in TEPR–switch-cost relationships were attributable to age differences , we entered participant age as a covariate into the regression and found nearly identical results, suggesting that our results were not driven by differences in participant age (see Supplemental Table S6). Of note, covarying out the effect of age revealed a significant interaction between NFC scores and TEPRs on baseline switch costs: TEPRs are a better predictor of baseline switch costs for those low in NFC ($\beta = 29.1472$, $SE = 14.0607$, $p = .03$; see Supplemental Table S6).

Reward-Induced Changes in Pupil Diameter and Task Performance

To further probe the effort account, we sought to test if individual differences in reward-induced switch cost reductions—interpreted as increased effort investment in accordance with incentives—could be predicted in pupil diameter. Since we did not observe significant changes in RT switch costs between the Low- and High-reward conditions, we elected to compare TEPRs between rewarded blocks (collapsed across low and high conditions) and the Baseline block. For each participant, we calculated 1) the difference in switch costs between rewarded and non-rewarded blocks and 2) the difference in switch-trial TEPRs between rewarded and non-rewarded blocks. Plotting these scores against each other (see Figure 4), we see that majority of the switch cost difference scores are negative—indicating reward-induced switch costs reductions—and these differences are tracked by changes to switch-trial TEPRs. Statistically, we observed a significant predictive relationship between reward-induced changes in switch trial TEPRs and reward-induced changes in switch costs indexed by a main effect of delta TEPRs on delta Switch Costs ($\beta = -31.0843$, SE = 13.1172, $p = .02$; see Table 5). This result provides further support for the effort account as it suggests that intra-individual, reward-induced modulations of effort are tracked by pupil diameter, while, critically, task demand remained constant.

Figure 6.

Scatter plot depicting the relationship between reward-induced changes in TEPRs on task switch trials, computed as the difference between rewarded and baseline blocks (horizontal axis) and reward-induced change in RT switch costs, computed as the difference between rewarded and baseline blocks (vertical axis).

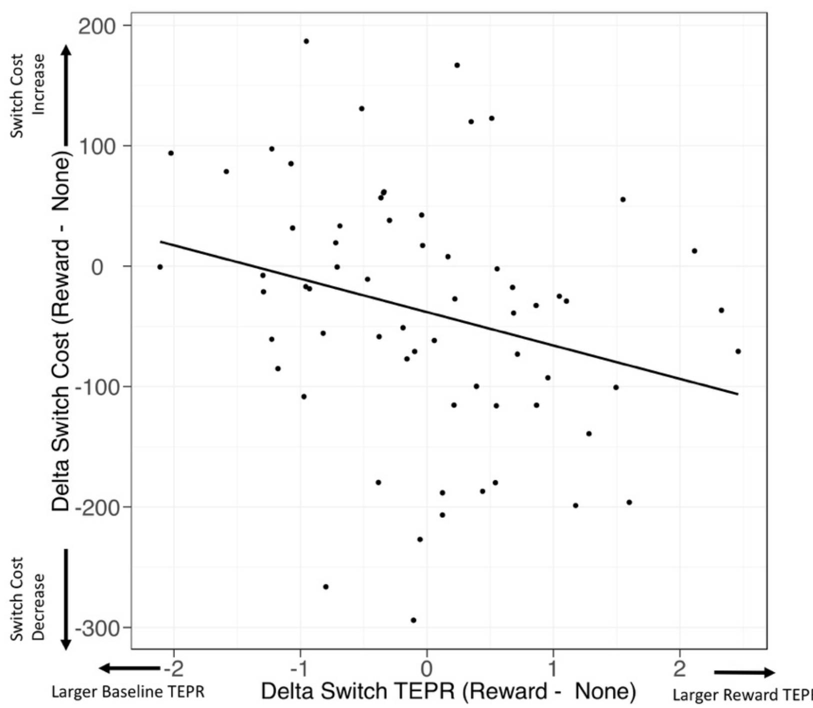


Table 5.

Linear regression coefficients indicating the influence of change in TEPRs, NFC scores, Stroop costs on reward induced changes in switch costs in the task-switching paradigm.

Predictors	Estimates	*SE*	*p*
(Intercept)	−37.8641	12.7085	.004*
Delta TEPR	−31.0843	13.1172	.021*
Stroop cost	2.2853	13.0106	0.861
NFC	−2.8281	13.0982	0.83
Reward presentation order	−3.8905	13.0287	0.766

Tonic pupil diameter

Finally, we sought to test whether reward-induced changes in arousal would manifest in tonic pupil diameter, operationalized here as the average raw pupil diameter during the baseline period of each trial. Indeed, as depicted in Fig. 7, we found that tonic pupil diameter increased linearly with reward incentive level ($\beta = 251.1978$, SE = 9.3582, $p < .001$; see Table 6), corroborating previous observations examining reward-induced tonic pupil diameter changes (Chiew & Braver, 2013; Heitz et al., 2008; MacLachlan & Howland, 2002). As above, we also sought to test whether tonic pupil diameter, measured during baseline and reward blocks, could be predicted on the basis of individual differences in Stroop RT costs or NFC, as previous work has shown tonic pupil diameter bears some relationship with both working memory ability (Heitz et al., 2008) and fluid intelligence (Van Der Meer et al., 2010). We failed to find a significant relationship between Stroop RT costs and tonic pupil diameter on baseline blocks ($\beta = 3.3240$, SE = 74.9657, $p = .95$), while higher NFC had a marginally significant predictive effect upon Baseline tonic pupil diameter ($\beta = -143.5890$, SE = 74.9709, $p = .05$).

Figure 7.

Average tonic pupil diameter during the three task-switching blocks. Error bars represent bootstrapped 95% confidence intervals. Individual dots represent participant-level data.

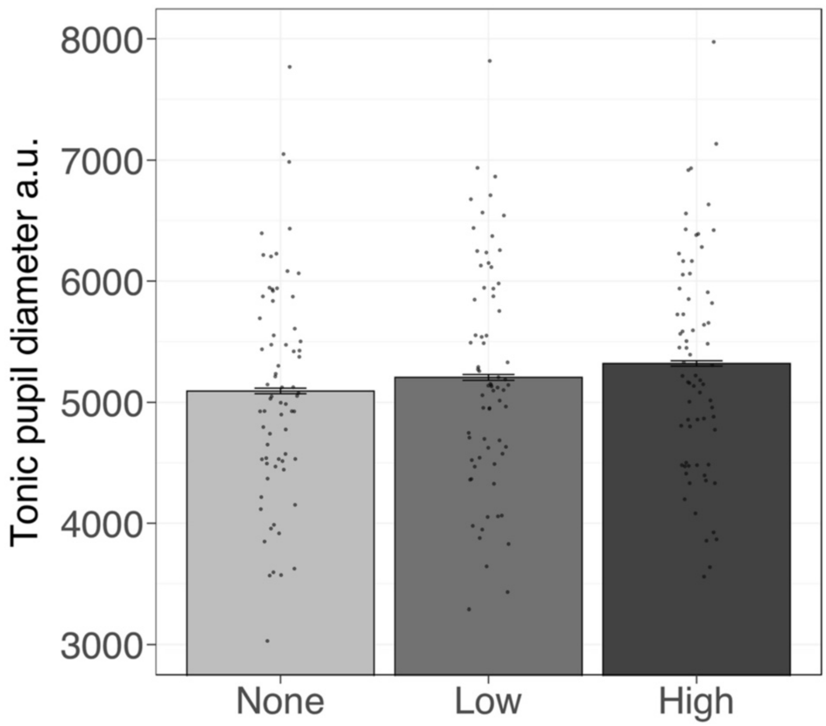


Table 6.

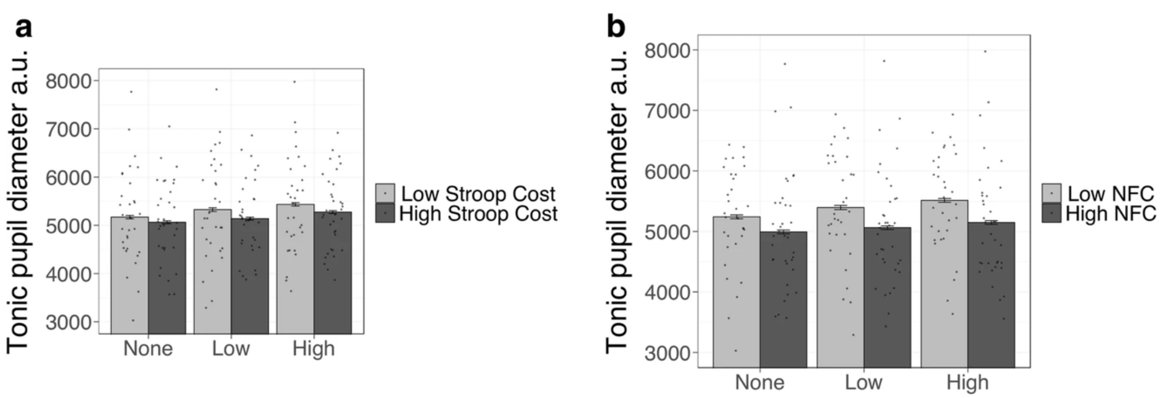
Mixed-effects regression coefficients indicating the influence of reward (0 = baseline, 1 = low reward, 2 = high reward), TEPRs, NFC scores, Stroop costs, and their interactions on tonic pupil diameter.

Predictors	Estimates	*SE*	*p*
(Intercept)	5,450.41	74.7646	<.001*
Reward	251.1978	9.3582	<.001*
Stroop cost	3.324	74.9657	0.965
NFC	−143.5890	74.9709	0.055
TEPR	−248.6662	8.803	<.001*
Trial	−1.1553	0.1682	<.001*
Reward × Stroop Cost	−2.8445	6.6682	0.67
Reward × NFC	−63.8837	8.3446	<.001*
Reward × TEPR	−39.7326	6.674	<.001*

Examining the reward blocks separately (see Fig. 8), we found reward-induced increases in tonic pupil diameter to be strongest in low-NFC individuals (reward NFC interaction, β = −39.7326, SE = 8.3446, p < .001), but did not depend on executive functioning ability (reward Stroop RT cost interaction; β = −2.8445, SE = 6.6682, p = .670). Finally, we tested whether phasic pupillary responses (i.e., TEPRs) related to tonic pupil diameter at the level of individual participants, observing a significant negative relationship (β = −248.6662, SE = 8.8030, p < .001). In other words, phasic changes in pupil diameter appeared largest for individuals whose tonic pupil diameter size was smallest, mirroring previous findings examining this tonic–phasic relationship (Gilzenrat et al., 2010). Further, this tonic–phasic relationship was moderated by reward incentives, such that higher available reward led to a stronger relationship between phasic and tonic pupillary responses (TEPR × Reward interaction, β = −39.7326, SE = 6.6740, p < .001). Again, to ensure these observed relationships were not driven by differences in age (MacLachlan & Howland, 2002), we added participant age as a covariate to this regression and found similar results, suggesting that the observed interaction between individual differences in intrinsic motivation and reward incentives was not attributable to differences in age (see Supplemental Table S7).

Figure 8.

a Average tonic pupil diameter by block type and grouping by median split Stroop costs. **b** Average tonic pupil diameter by block and grouping by median split Need for Cognition (NFC) scores. Error bars represent bootstrapped 95% confidence intervals. Individual dots represent participant-level data



Section 2.4 Discussion

While a considerable body of results has pointed toward using task-evoked pupillary responses (TEPRs) as a potential index of cognitive effort (Laeng et al., 2011; Rondeel et al., 2015; Van Der Meer et al., 2010), other work suggests that pupil diameter reflects task demand level (Beatty, 1982; Hershman & Henik, 2019; Kahneman & Beatty, 1966). Here, we sought to arbitrate between the effort and demand accounts of pupil dilations, by measuring TEPRs while holding task demand constant and examining how individual differences in task switch costs—a behavioral maker of effort investment—relate to task-evoked pupillary responses both at baseline and in response to changes in reward incentives.

First, upon examining the interrelationship between individual differences in task performance and pupillary responses at baseline—in the absence of reward incentives—we found that larger TEPRs on switch trials predicted smaller task switch costs. In other words, holding task demand constant, larger pupillary responses predicted better task-switching performance across individuals. This result provides compelling support for the effort account and complements previous work that has similarly found improved task performance to be associated with larger phasic pupil diameter (Rondeel et al., 2015; Van Der Meer et al., 2010). At the same time, we found evidence in support of the demand account, as TEPRs were larger on more demanding task switch trials, mirroring previous findings that highlight the positive relationship between TEPRs and task demand (Katidioti et al., 2014; Rondeel et al., 2015). Taken together, this pattern of observed results suggests that TEPRs can potentially provide unique information about an individual's effort outlay, over and above task demand level.

Second, we observed that the relationship between TEPRs and task switch costs at baseline was strongest for those low in EF capacity (as measured by Stroop interference effects). In other words, individual effort costs—stemming from either cognitive processing limitations, intrinsic motivation to expend effort, or both (Inzlicht et al., 2018)—appeared to moderate the observed relationship between this putative physiological measure of effort (TEPR) and the behavioral consequences of effort (task switch costs), highlighting the usefulness of examining individual differences. Again, these results are difficult to explain with a pure task demand interpretation of TEPRs, as we did not find that either these trait measures could predict task switch costs at baseline (see Table 4). Instead, this pattern of results could suggest that the observed variability in task performance reflects heterogenous levels of effort investment across the entire sample—for example, for those with the lowest EF capacity, variability in task performance may arise from increased processing of task-relevant information, while for those high in ability, variability in task performance may be harder to account for. This observation dovetails with past work finding that individuals low in working memory capacity also had larger phasic pupillary responses while completing a demanding working memory task (Heitz et al., 2008). Similarly, with respect to intrinsic motivation to exert effort—as measured by the NFC scale—we found suggestive, but statistically marginal, evidence that individual differences in TEPRs for lower NFC individuals more strongly predicted task-switching performance. Third, we tested whether these observed individual differences in effort exertion, in response to increasing performance-contingent rewards (i.e., reward vs. baseline) were related to reward-induced changes in TEPRs. In accordance with the notion of a cost-benefit trade-off guiding effort investment (Shenhav et al., 2017), we found that reward-induced decreases in task switch costs—interpreted as increased effort investment in accordance with incentives—were also predicted by individual differences in reward-driven TEPR modulations. This observation provides particularly compelling evidence for the effort account, as comparing TEPRs within participant addresses any concerns of potential confounds that may arise when comparing between individuals or groups (e.g., ambient lighting, age; van der Wel & van Steenbergen, 2018).

It is worth noting that while reward incentives have previously been shown to increase pupil diameter on demanding working memory and cognitive control tasks (Bijleveld et al., 2009; Chiew & Braver, 2013, 2014), the current study builds on these findings and demonstrates that reward-induced changes in pupil diameter relate to behavioral changes, further providing evidence that pupil diameter reflects increased effort investment. These findings extend our previous work, revealing how EF capacity and NFC differentially predict reward-induced cognitive effort modulations, measured behaviorally with task switch costs (Sandra & Otto, 2018). Here, we found that individual differences in presumed effort costs (i.e., EF capacity) also bear upon the strength of the relationship between behavioral and pupillary measures of effort exertion, and in doing so, compellingly suggest that TEPRs might, in principle, provide a window into cost-benefit effort computations that may not be observable with behavioral measures alone.

Our results are difficult to reconcile with a demand account of task-evoked pupillary responses, as they suggest that intraindividual modulations in performance can be tracked by pupillary responses. It is possible that the observed lack of an effect between high-reward and low-reward conditions can be attributable to the small difference in reward values (i.e., 1 cent vs. 10 cents per correct response) used here, or the use of a blocked design rather than employing trial-by-trial variation in rewards (cf. Fröber & Dreisbach, 2016; Kleinsorge & Rinkenauer, 2012; Shen & Chun, 2011). This is consistent with past work also finding equivocal evidence for the ability of reward incentives alone to reduce switch costs (e.g., Aarts et al., 2014). Here, as in our previous work, the increase in potential rewards in high-reward versus low-reward trials may not be sufficient to increase effort outlay alone, but it was large enough to elicit differences between individuals in reward-induced effort expenditure (Sandra & Otto, 2018). Relatedly, in the specific reward incentive manipulation used here, task-switching performance at baseline (i.e., without incentives) was measured prior to performance in rewarded blocks, following designs employed in previous investigations of motivated cognitive control (Chiew & Braver, 2013, 2014; Fröber & Dreisbach, 2016). While the fact that all participants performed the baseline block first could potentially contribute to a practice effect—after controlling for linear effects of trial number and block order in our regression models—we should note that we observed no significant effects of mini-block order upon switch costs (see Table 4), suggesting that performance did not merely improve as a result of practice over successive trial blocks, perhaps owing to the practice participants underwent prior to the baseline blocks. Similarly, we find that while participants' RTs generally decreased over the course of the experiment, TEPRs remained stable (see Table 3) suggesting the observed reward-induced TEPR changes were not driven by practice effects. In terms of accuracy, while participants showed slight improvements over the course of the entire experiment (see Supplemental Table S5), these improvements were not found to be significant when comparing the reward blocks (see Supplemental Table S4). Future work investigating rewarded-guided effort allocation should employ designs that carefully control order effects to firmly rule out the possibility that apparent reward-induced changes in behavior and physiological responses arise from practice.

It is also worth noting that task switch costs are thought to reflect two constituent processes: a task set reconfiguration cost accompanying task switches, which can be reduced by increasing preparatory or proactive control, and a residual switch cost, thought to arise from reactive control processes stemming from task set interference (Kiesel et al., 2010). While the task-switching paradigm employed in the present experiment was not designed to disentangle the specific form of effortful control—proactive versus reactive—presumably reflected by TEPRs, we speculate that effort-linked TEPRs observed here might uniquely reflect a proactive component, on the basis of a body of previous work linking TEPRs to proactive control adjustments in continuous performance tasks (Chiew & Braver, 2013, 2014). Of course, future work leveraging more specialized task-switching paradigms that can adjudicate between reconfiguration and residual switch costs is necessary to resolve which specific form(s) of effortful control—proactive and/or reactive—TEPRs index. Relatedly, while the present study did not employ a task precue, providing task cues in advance of the stimulus permits individuals to engage in advance preparation for task switches, which as the result of reducing task switch costs (Kiesel et al., 2010; Monsell & Mizon, 2006). Accordingly, while the present experimental design is unable to conclusively link TEPRs to (effortful) preparatory processes that occur *in advance* of stimuli but rather speak to effort investment at the time of stimulus presentation, future research should probe (1) the relationships between switch costs and TEPRs under baseline and reward conditions in a task-switching paradigm employing precues, and (2) how parametrically manipulating the cue-stimulus interval might alter these observed relationships between switch costs and TEPRs.

Finally, we also sought to test whether changes in arousal state or task engagement would manifest in tonic pupil diameter (Unsworth & Robison, 2018). We hypothesized that increasing reward would result in upregulation of arousal, resulting in larger tonic pupil diameter, following previous findings (Chiew & Braver, 2013, 2014; Hopstaken et al., 2015). Confirming our hypotheses, we found that reward incentives increased tonic pupil diameter, suggesting that this measure correlates to one's overall state of arousal and is perhaps indicative of the use of more proactive (i.e., sustained) rather than reactive (i.e., transient) control processes (Braver, 2012; Chiew & Braver, 2013) in task-switching.

Given these results indicating that tonic pupil diameter could index one's attentional state, we also sought to test whether individual differences in executive functioning and intrinsic motivation for exerting effort were reflected in tonic pupil diameter. While we did not observe robust relationships between tonic pupil diameter and EF capacity, individual differences in intrinsic motivation (measured with the NFC scale) were found to modulate the effect of reward on tonic pupil size. Specifically, reward-induced changes in tonic pupil diameter were strongest for those low on intrinsic motivation to exert effort, suggesting that reward incentives offset their aversion to exert cognitive effort and led them to increase general task engagement vis-à-vis arousal. However, we did not observe a significant relationship between EF capacity and reward-induced increases in tonic pupil diameter.

Of note, while our phasic pupil diameter analyses found that individual differences in EF capacity and NFC were found to moderate the relationship between performance and TEPRs, we failed to find predictive effects of tonic pupil diameter upon performance. This pattern of results suggests that phasic and tonic measures might index separable psychological constructs, (i.e., momentary effort investment vs. a more sustained arousal state) as was previously suggested (Chiew & Braver, 2013, 2014; Unsworth & Robison, 2018). More generally, while our results speak to the importance of measuring both individual differences in EF and intrinsic motivation, it should be noted that our Stroop-based measure of EF is not domain general but rather is specific to the inhibition component of EF (see Miyake et al., 2000). Thus, future work should examine the extent to which the observed relationships between EF, task performance and reward responsiveness generalize to other components of EF (e.g., updating and set-shifting) or if they are specific to the facet of EF indexed by Stroop interference (i.e., inhibition).

Recently, it has been theorized that the relationship between limited working memory capacity and performance on executive control tasks is mediated by a dysregulation in the locus coeruleus-norepinephrine system, which in turn is thought to lead to greater default-mode network activity and lapses in attention (Unsworth & Robison, 2017). At the same time, pupil diameter has been previously linked to locus-coeruleus norepinephrine functioning (Joshi et al., 2016), which, in turn, is thought to be modulated in response to increasing arousal (e.g., via increasing task demands; Aston-Jones & Cohen, 2005). Thus, pupil diameter is thought to index momentary shifts in neuronal gain driven by modulations in norepinephrine functioning (Aston-Jones & Cohen, 2005; Nieuwenhuis et al., 2011) and has also been previously shown to decrease with off-task thoughts (i.e., mind-wandering, distraction, inattention; Unsworth & Robison, 2016). These phasic pupil-linked changes in norepinephrine-mediated attentional state also lend support to the effort account of pupil diameter, as it has been found that the trials in which participants report greatest task engagement are also trials with the largest TEPRs (Unsworth & Robison, 2016). Finally, we observed a negative relationship between tonic pupil diameter and phasic pupillary responses, which was further modulated by reward. These observations buttress the putative norepinephrine-dependent trade-off between control states (i.e., task engagement vs. disengagement; Gilzenrat et al., 2010), and suggest that perhaps monetary incentives alter task performance through locus coeruleus functioning.

Overall, our results weigh in favor of an effort account of TEPRs, suggesting that pupil diameter, under controlled circumstances, can serve as viable index of cognitive effort investment in cognitive control tasks, and, in turn, that pupil measurements can inform models of the regulation of effortful cognitive processing. Given the theorized neural basis for nonluminance mediated pupil diameter changes, our results further suggest potential neural correlates of metacontrol. As previously discussed, it is thought that changes in pupil diameter reflects locus-coeruleus norepinephrine mediated changes in arousal state. These changes in norepinephrine are thought to be driven by the anterior cingulate cortex (ACC; Aston-Jones & Cohen, 2005) which has been previously implicated in signaling the need for increased cognitive control (Botvinick et al., 2004; Braver et al., 2001; Carter & Van Veen, 2007). Interestingly, it has also been shown that, to some degree, pupil dilations in nonhuman primates correlate with spontaneous ACC firing, and in some cases precedes pupil-linked modulations of locus coeruleus neuronal activity (Joshi et al., 2016). More recent theories of ACC function posit that the ACC allocates cognitive control by weighing the relative costs of exerting control and the benefits (i.e., rewards) potentially conferred by successfully completing one's goal (Shenhav et al., 2013, 2016). Mirroring this view, our results indicate that offsetting the costs of control, by increasing reward incentives, not only improved task performance but was also tracked by increases in pupil diameter. Together, these results suggest that task performance reflects the momentary decisions to exert cognitive control based on the relative costs and benefits, which are reflected in modulations of phasic pupil diameter. Future work should directly investigate the interrelationship between TEPRs, ACC activity, and both interindividual and intraindividual variation in EF capacity, intrinsic motivation, and performance on cognitive control tasks.

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Section 2.6: Supplemental Materials

Table S1.

Mixed-effects regression coefficients indicating the influence of trial type (congruent vs incongruent) on log RTs in the Stroop Interference task.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	6.4408	0.0180	<0.001
Incongruent	0.2578	0.0115	<0.001
Prev. Incorrect	0.0351	0.0096	<0.001
Prev. Incongruent	0.0128	0.0035	<0.001
Key Repetition	-0.0312	0.0051	<0.001
Prev. Missed	-0.0250	0.0135	0.063
trial	0.0000	0.0002	0.776

Table S2.

Logistic mixed-effects regression coefficients indicating the influence of trial type (congruent vs incongruent) on response (correct vs incorrect) in the Stroop Interference task.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	5.0362	0.3235	<0.001
Incongruent	-1.7928	0.1803	<0.001
Prev. Incorrect	-0.2183	0.1880	0.246
Prev. Incongruent	-0.0011	0.1083	0.992
Key Repetition	0.0815	0.0988	0.410
Prev. Missed	0.4326	0.3179	0.174
trial	-0.0026	0.0028	0.356

Table S3.

Mixed-effects regression coefficients indicating the influence of trial type (task switch versus task repeat), reward level (low vs. High), and the interaction between Reward and trial type on RTs in the task-switching paradigm.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	6.9332	0.0259	<0.001
Switch (vs Repeat)	0.1243	0.0092	<0.001
Reward (High vs Low)	-0.0188	0.0101	0.064
Trial	-0.0001	0.0001	0.193
Task (Magnitude vs Parity)	0.0238	0.0058	<0.001
Prev. Switch	0.0088	0.0023	<0.001
Prev. Missed	-0.0089	0.0164	0.588
Prev. Incorrect	0.0098	0.0057	0.085
Prev. Response same	-0.0224	0.0026	<0.001
Bar (above vs below)	-0.0099	0.0058	0.085
Congruent	-0.0518	0.0100	<0.001
Switch * Reward (High vs Low)	-0.0087	0.0083	0.298

Table S4.

Mixed-effects logistic regression coefficients indicating the influence of trial type (task switch versus task repeat), reward level (low vs. High), and the interaction between Reward and trial type on responses (correct vs incorrect) in the task-switching paradigm.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	2.4581	0.2691	<0.001
Switch (vs Baseline)	-0.3476	0.0982	<0.001
Reward (High vs Low)	0.4613	0.1191	<0.001
Trial	0.0013	0.0007	0.081
Task (Magnitude vs Parity)	-0.2479	0.0626	<0.001
Prev. Switch	-0.0453	0.0400	0.257
Prev. Missed	-0.2867	0.2006	0.153
Prev. Incorrect	0.1352	0.1006	0.179
Key Repetition	0.0578	0.0370	0.119
Bar (Above vs below)	0.0200	0.0626	0.749
Congruent	1.5841	0.1565	<0.001
Switch (vs Repeat) x Reward (High vs Low)	-0.1277	0.1503	0.395

Table S5.

Mixed-effects logistic regression coefficients indicating the influence of trial type (task switch versus task repeat), reward level (Reward vs. None), and the interaction between Reward and trial type on responses (correct vs incorrect) in the task-switching paradigm.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	2.4730	0.1790	<0.001
Switch (vs. Repeat)	-0.4508	0.0937	<0.001
Reward (vs. Baseline)	0.2863	0.1356	0.035
Trial	0.0013	0.0006	0.035
Task (magnitude vs Parity)	-0.2936	0.0559	<0.001
Prev. Switch	-0.0326	0.0309	0.292
Prev. Missed	-0.1965	0.1312	0.134
Prev. Incorrect	0.0298	0.0560	0.594
Prev. Response same	0.0230	0.0301	0.445
Bar (above vs Below)	0.0153	0.0559	0.784
Congruent	1.2067	0.1125	<0.001
Switch x Reward	0.0558	0.1194	0.640

Table S6.

Mixed-effects regression coefficients indicating the influence of TEPRs, NFC scores, Stroop Costs and their interactions on mini-Block Switch Costs in the baseline block of the task-switching paradigm, controlling for age.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	181.7356	96.4765	0.060
Age	0.4749	4.1689	0.909
TEPR	-27.1290	12.1365	0.025
Stroop Cost	8.6575	12.1439	0.476
NFC	10.5055	13.0492	0.421
Trial mini-Block	-8.9553	10.3102	0.385
TEPR x Stroop Cost	-29.5429	11.4993	0.010
TEPR x NFC	29.1472	14.0607	0.038

Table S7.

Mixed-effects regression coefficients indicating the influence of Reward (0: Baseline, 1: Low Reward, 2: High Reward), TEPRs, NFC scores, Stroop Costs and their interactions on tonic pupil diameter, controlling for age.

Predictor	*Estimate*	*SE*	*p*
(Intercept)	6261.6765	573.0688	<0.001
Reward	250.2746	9.4239	<0.001
Stroop Cost	-23.4519	77.1955	0.761
NFC	-125.3013	80.2295	0.118
TEPR	-247.7645	8.8594	<0.001
Age	-36.6238	25.7677	0.155
Trial	-1.1411	0.1705	<0.001
Reward * Stroop Cost	-3.0574	6.6880	0.648
Reward * NFC	-61.7912	8.5420	<0.001
Reward * TEPR	-39.7337	6.7273	<0.001

Section 3: Bridging Text

Having a measure of effort investment, independent of task demands, and task performance is important as it allows us to investigate the deployment of cognitive effort independently. The literature has taken three broad approaches to measure cognitive effort investment: 1) subjective ratings, 2) task performance, and 3) physiological reactions. Critically, these different approaches tap into three distinct aspects of cognitive effort exertion.

Subjective ratings have long been a method psychologists use to measure individuals' experiences and provide insight into the subjective experience of participants. For cognitive effort, this has taken the form of the National Aeronautics and Space Administration—Task Load Index (NASA-TLX) which asks participants to retroactively reflect on one's feelings of demand and exertion (Hart, 2006). Previous research has used this measure to index how much effort participants subjectively felt they invested (Crawford et al., 2023; Grier et al., 2003; Krejtz et al., 2018), yet it remains unclear whether these feelings of demand and exertion reflect the inherent costs of effort exertion or the value of control which integrates effort costs and available rewards (Devine et al., 2022; Kurzban, 2016; Saunders et al., 2017). Thus, while subjective report measures can help corroborate retrospective metacognitions, they are limited in their ability to capture momentary changes in effort exertion.

The cognitive control literature has equally used task performance as a proxy for effort investment. Of particular interest accuracy in responding and response times have often been used under the assumption that effort investment and task performance share a positive, monotonic relationship. However, this often-used assumption may sometimes be violated for tasks where task performance is not contingent on effort investment (Otto et al., 2022).

Furthermore, value-based decisions are by nature subjective, meaning there is no externally defined correct response. While experimenters often use Expected value maximizing choice as a proxy for accuracy in value-based choice (da Silva Castanheira, Fleming, et al., 2021; De Martino et al., 2013; Zysset et al., 2006), this assumes the goal of the decision-maker is to maximize economic gain and not some other quantity (i.e., subjective utility). Importantly, without a measure of response accuracy, it is difficult to tell whether response speeding reflects effort investment or disengagement. For example, previous work on value-based choice has found overall rewards on offer lead to response speeding which has been interpreted as evidence of effort disengagement (Frömer et al., 2019; Pirrone et al., 2018). This pattern of response times has equally been interpreted as effort investment in the cognitive control literature, as seen in Section 2. Together, this makes task performance as a proxy for effort investment an impractical measure in value-based choice.

Finally, experimenters have also turned to physiological measures to index momentary cognitive effort expenditure. In the previous section, we provided evidence that the effort account of pupil diameter by leveraging individual differences in effort costs and reward-induced changes in task performance. We showed that task-evoked pupil dilations related to both between-individual differences in effort costs, indexed by measuring capacity for cognitive control capacity using the Stroop Interference task. We also showed that reward-induced increases in task performance, indexed by smaller switch costs, tracked changes in pupil diameter. Together these results suggest that pupil diameter can be used as an online measure of effort exertion. Thus, in the following section, we will use pupil diameter to index effort expenditure in value-based decision-making to test whether demanding choices are avoided, and effort investment can predict demand avoidance.

Section 4: Measuring Effort in Value-Based Choice

Section 4.1: Introduction

The decisions we encounter daily feel mentally taxing. Whether the choice we face is perceptual (i.e., *how do I adjust my information processing to achieve my goals?*) where responses are based on external criteria or value-based (i.e., *how do I weigh costs and benefits to choose?*) where responses are based on internally-defined preferences (Smith & Krajbich, 2021; Hanks & Summerfield, 2017; Padoa-Schioppa & Schoenbaum, 2015; Shadlen & Shohamy, 2016). Yet, prominent theories of mental effort in psychology often overlook value-based choices like risky decision-making (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018). Intuitively, extensively deliberating between investment portfolios feels more effortful than consulting a financial advisor. Why some risky decisions are experienced as demanding but not others, and why we sometimes decide to use more effortful decision strategies while other times avoid deliberation remains unclear. Thus, we aim to understand: 1) whether we can experimentally manipulate value-based choice task demands, 2) whether demanding risky value-based choices are avoided and 3) does momentary effort exertion predict demand avoidance in risky decision-making.

Cost-benefit models of effort allocation predict that cognitive effort is aversive and should be avoided when all else is equal (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018). Yet, the data supporting cognitive effort avoidance pertains entirely to the deployment of cognitive control (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010; McGuire & Botvinick, 2010; Vogel et al., 2020; Westbrook & Braver, 2015) despite this principle often serving as a foundational assumption in the value-based decision-making literature (see Anderson, 2003 for a review). Thus, it remains unclear whether risky decisions can also be experienced as demanding and therefore avoided.

Can value-based choice task demands be experimentally manipulated?

Experimenters have leveraged two major methods to increase the demand of choices—either by manipulating features of the environment or features of the choice set itself. In terms of environmental features, one method is to limit the ability to execute time-consuming deliberation either via manipulations of time pressure (Guo et al., 2017; Hu et al., 2015; Madan et al., 2015; Olschewski & Rieskamp, 2021; Zur & Breznitz, 1981) or increasing the tax on individuals' cognitive load (Hinson et al., 2003, 2019; Whitney et al., 2008). These manipulations are thought to increase participants' reliance on heuristics—decision strategies which conserve information processing (Gigerenzer & Gaissmaier, 2011). However, using these manipulations to increase task demands assumes that participants engage in more demanding deliberation when there are no environmental constraint rather than continuing their use of heuristics. In terms of choice features, previous work has focused on manipulating the discriminability the amount of information. Aligned with the expected value (EV) maximizing view of choice (Allais, 1953), others have used the similarity in (expected) value between options (i.e., discriminability) as a manipulation of decision demand (da Silva Castanheira, Fleming, et al., 2021; Lebreton et al., 2009; Lee & Daunizeau, 2021; Zysset et al., 2006). Yet, with risky choices the same level of discriminability between options can sometimes seem harder and engender lower self-reported subjective confidence (da Silva Castanheira, Fleming, et al., 2021). Aligned with information-processing approaches to decision-making which assume that effort scales positively with the amount of information to be processed, researchers have either increased the number of options (Iyengar & Lepper, 2000) or the complexity of the options (Bernheim & Sprenger, 2020; Huck

& Weizsäcker, 1999; Sonsino et al., 2002; Zilker et al., 2020). Thus, the greater amount of information to consider when deciding, the more difficult the decision. However, these approaches are largely agnostic to the degree of cognitive control heuristics requires to execute.

The value-based decision-making literature has used various approaches to operationalize the cognitive effort of a heuristic, often producing contradictory interpretations. Effort reduction approaches to value-based choices, like dual process (Diederich & Trueblood, 2018; Evans & Stanovich, 2013) theories and information processing approaches (Busemeyer & Townsend, 1993; De Martino et al., 2013; Krajbich & Rangel, 2011; Roe et al., 2001), assume that effort is what is being conserved when fast responses are executed. This assumption follows from work on process tracing techniques in decision-making which defined the effort required to execute a given decision process as the number of Elementary Information Processes (EIP) (Johnson & Payne, 1985; Payne et al., 1993) needed to choose e.g., putting an option's attribute value in working memory and contrasting options by subtracting summed attribute values. However, it is particularly difficult to determine the effort required to implement a heuristic from first principles, as parsing information into discrete units may be arbitrary and depend on the level of granularity (Thomson & Oppenheimer, 2021). Furthermore, the EIP approach fails to account for the cognitive processes (e.g., cognitive control, working memory, attention) needed to implement heuristics which may depend on situational factors. For example, Bobadilla-Suarez & Love (2018) found that, while the Take-The-Best heuristic uses information more frugally by choosing based on the first discriminatory cue between option, it takes longer to implement and fares worse under time pressure than more deliberative strategies. Thus, it is difficult to predict the demand of a heuristic for a given choice set and context.

Are Demanding value-based choices avoided?

The literature on value-based choice has developed in large part on the assumption of effort minimization: decision-makers will employ strategies to reduce the cognitive demands of choice. Indeed, it is reasonable to assume that value-based decisions which tax cognitive resources are avoided as they rely on the same resources as cognitive control (Hinson et al., 2019; Whitney et al., 2008). Yet most of the evidence we have for this effort minimization principle in value-based choice has been indirect and is mainly supported by the heuristics and biases literature, which suggests that people avoid difficult deliberation by employing simplifying decision strategies (Gigerenzer & Selten, 2002; Goldstein & Gigerenzer, 2002; Payne et al., 1993). For example, people will often prefer no change or default options (Inman & Zeelenberg, 2002; Samuelson & Zeckhauser, 1988; Tsiros & Mittal, 2000), no action (omission bias, Ritov & Baron, 1992; inaction inertia, Tykocinski et al., 1995), and delay (choice deferral, Dhar, 1996). Additionally, features of the choice can also influence preferences: people avoid complex options (Zilker et al., 2020) or even avoid selecting altogether when there are too many options (Iyengar & Lepper, 2000). It is often assumed that the use of these strategies is more frugal in terms of time and resources. Yet, while heuristics require less information, they also may require more attentional control needed to execute these heuristics (Bobadilla-Suarez & Love, 2018). The use of heuristics remains a purported index of effort avoidance. Thus, it is unclear whether the choices researchers think are more demanding are in fact subjectively experienced as demanding and whether in turn these more demanding choices are truly avoided. To address these concerns, we leverage online physiological measures of effort exertion (da Silva Castanheira, LoParco, et al., 2021).

Does effort exertion predict demand avoidance?

It equally remains unclear whether the use of heuristics truly reflects the optimization of effort costs or some other quantity like feelings of confidence (Lee & Daunizeau, 2021). To help disambiguate these accounts, we use pupil diameter as an online measure of effort exertion during value-based choices. Importantly, most of the work on effort and pupillometry has largely focused on cognitive control with little work investigating the relationship in value-based decisions (da Silva Castanheira et al., 2021). While there is some evidence that pupillary responses may track effort investment in value-based decisions (Eldar et al., 2021), there is other evidence suggesting pupil dilations may reflect reward on offer (Bray et al., 2008; J. P. O'Doherty et al., 2003), risk (Lavín et al., 2014), or even surprising outcomes (Preuschoff et al., 2011; Van Slooten et al., 2018)—making it difficult to infer effort investment from increases in pupil diameter in risky decision-making tasks where these factors vary.

The present experiments

Here, we present three experiments around a new behavioural paradigm we call the *decision avoidance task (DAT).* In the first experiment, we validate the hypothesis that strategic conflict between heuristics in value-based choice is experienced as demanding by leveraging performance and subjective ratings of task demands. Using the demand ratings from the first experiment we create two choice sets of high and low task demands controlling for other important features in the DAT. In the DAT participants are asked to complete two phases: the learning where stimulus-stimulus associations are learned and test phase where they are free to choose which choices (i.e., high vs low demand) they prefer. In second experiment, participants were asked to learn an association between a stimulus and one of the two choice sets (i.e., high vs low demand) and then given the choice between the paired stimuli in a subsequent task phase.

We predict that participants will develop a strong tendency to avoid the stimulus associated with the choice set previously rated as demanding. Finally, in a third experiment, we asked participants to complete the DAT while measuring momentary effort exertion as indexed by their pupil diameter. We predict that those who exerted the most effort in the learning phase indexed by larger pupil diameter will also develop the strongest avoidance of demand in the test phase. Together, these experiments will help corroborate whether demanding risky decision are aversive, avoided and truly elicit greater effort exertion.

Section 4.2: Experiment 1

In this first experiment, we seek to test whether risky decisions with low discriminability and high strategic conflict elicit changes in task performance (i.e., EV maximizing choice and response times) and are experienced as subjectively more demanding. To this end, we asked participants to complete a typical risky decision-making task and rate the demand of these choices using the standard demand scale from the NASA Task Load Index (Hart, 2006). These ratings allow us to test whether participants experience the choices labelled as difficult—designed to elicit greater strategic conflict—as more demanding and engendering less confidence.

Methods

Participants

Data were collected from 37 healthy young adults (5 males, M_{age} = 20.18, SD_{age} = 1.32) who were recruited via the McGill Participant pool and asked to complete several tasks for course credits and a cash bonus of $5. Of the 37 participants, data from 3 participants failed to record properly resulting in a sample of 34 participants. Of the 34 participants, we further excluded the data from one participant who failed to choose the EV maximizing option for the easy choices more than 60% of the time, resulting in a final sample of 33.

Materials and Procedure

Participants were asked to complete two computerized tasks measuring cognitive ability: the Digit Symbol Coding Task (Kail & Salthouse, 1994; Mathias et al., 2017) and the Operation Span task (Unsworth et al., 2005). Participants were then asked to complete a risky decision-making task—the main task of interest (da Silva Castanheira, Fleming, et al., 2021; da Silva Castanheira, Sharp, et al., 2021). After the tasks, participants were asked to answer 3 questionnaires in a randomized order to measure individual differences: The Maximization Scale (Nenkov et al., 2008), the Need for Cognition Scale (Cacioppo et al., 1984), and the State-Trait Anxiety Inventory (STAI) (Spielberger, 1983). For more information on the individual difference measures please refer to the supplemental materials.

Risky Decision-Making Task

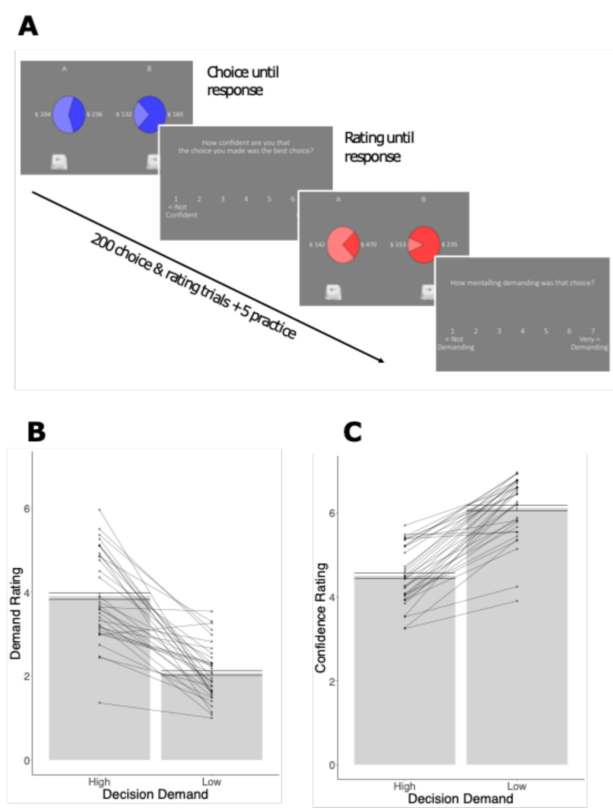
To assess participants' subjective feelings of demand when choosing between difficult or easy decisions, we asked participants to complete a risky decision-making task. The decision-making task consisted of a series of risky choices presented to the participants as possible monetary rewards represented as two side-by-side pie charts (da Silva Castanheira, Fleming, et al., 2021; da Silva Castanheira, Sharp, et al., 2021; Guo et al., 2017). Each option consisted of two possible outcomes and their associated chances of occurring (see Figure 1). Responses to these choices were self-paced. Importantly, participants were instructed that they would be paid a cash bonus in proportion to their total earnings on the risky decision-making task at the end of the experiment and consequently had to choose options to maximize their bonus. However, at the end of the experiment, all participants were remunerated the same amount: $5.00.

Critically, we manipulated task demands via decreasing discriminability in Expected value and assessed whether our manipulation engendered feelings of higher task demand. We used similarity in desirability to manipulate decision conflict by changing the differences in Expected Values (EV) between the options (Venkatraman et al., 2009). Expected value is defined as the weighted average of an options' outcomes by their associated probabilities—the long-run average outcome of a gamble. If the options differed in EV (i.e., non-zero difference in EV; min= 32, max=220), we considered the choice easy (e.g., 45% chance of $450 and $179 otherwise, EV= 300.95; versus 55% chance of $365 and $94 otherwise, EV= 243.05). Meanwhile, if both options had similar EVs was near zero (i.e., near zero difference in EV; min= 0, max=0.76), we considered the choice harder (e.g., 84% chance of $355 and $250 otherwise, EV= 338.2; versus 35% chance of $611 and $192 otherwise, EV= 338.65). Importantly, for the easy stimuli where there was a larger non-zero difference in EV, we ensured that both options (i.e., left vs right) were equally favored resulting in an overall mean difference in EV of approximately 0 (see Table S3). However, here the perceived difficulty of a choice depended on both the choice and the decision strategy being used, as participants may not only be using differences in EV to choose. Thus, decision-makers using any other strategy may not find choices with similar in EV demanding.

To account for the variability in possible heuristic use, we considered two well-known heuristics that subjects may be relying on if they are not computing differences in EV: Maximin and Maximax. The Maximin heuristic predicts that decision-makers should maximize the minimum possible—select the option with the best of the worst outcomes (Coombs et al., 1970). Contrastingly, the Maximax heuristic predicts that decision-makers should maximize the maximum possible gain—select the option with the best of the best outcomes (Coombs et al., 1970). Importantly, unlike EV maximization, both these heuristics are agnostic toward outcomes probabilities and focus solely on the outcomes themselves. Here, we ensured that hard choices presented a conflict between the Maximin and Maximax heuristics such both heuristics would suggest different choices (e.g., Option 1: 45% chance of winning $392 and $146 otherwise; versus Option 2: 80% chance of winning $269 and $208 otherwise; where Maximin predicts option 2 Maximax predicts option 1), whereas the easy choices presented no conflict between the Maximin and the Maximax heuristics (e.g., Option 1: 32% chance of winning $116 and $129 otherwise; versus Option 2: 29% chance of winning $74 and $87 otherwise; where both Maximax and Maximin predict option 1). One key component of cognitive control is the selection of relevant responses and inhibition of prepotent but inappropriate responses. To control for any other choice features (the coefficient of variation, the standard deviation of the outcomes etc.,) possibly contributing to demand and confidence ratings, we ensured both hard and easy problems were equated in terms of total reward on offer, outcome probabilities, their coefficient of variation, their expected values and the standard deviation of the outcomes (see Tables S1-S3).

Figure 1.

A Schematic depicting the risky decision-making task. Participants were asked to decide between two risky options for whose outcomes and associated probabilities were depicted as pie charts. Choices were recorded using the right and left arrow keys. After each choice, participants were presented asked to rate how demanding ("How mentally demanding was that choice?") or how confident ("How confident are you that the choice you made was the best choice?") they were on a 7-point Likert scale using the numbers on the keyboard. Results of the risky decision-making task. **B** Subjective feelings of confidence also varied by choice difficulty: easy choices were rated as engendering higher subjective confidence when compared to difficult choices. **C** In terms of subjective feelings of demand, participants rated the difficult choices are more demanding than the easy choices.



After each choice, participants were asked either to rate how demanding the preceding choice was ("*How mentally demanding was that choice*") (Hart, 2006) or how confident they felt in having made the best choice ("*How confidence are you that the choice you made was the best choice?*") (da Silva Castanheira, Fleming, et al., 2021). The rating following each choice alternated randomly whereby half the choices were followed by demand ratings. Subjective ratings were collected on a Likert scale from 1-7, where 1 indicated not being confident/not demanding, and 7 indicated being extremely confident/demanding. Responses were recorded using the number keys 1 through 7.

Data Analysis

We used linear mixed-effects regressions to test how decision difficulty (Easy vs Hard) affected subjective ratings. For both the confidence and demand regressions, we modelled Likert-scale ratings as a function of dummy coded task demand (1=hard, 0=easy), RTs Z-scored both within-person as well as the interaction between RTs and task difficulty. To assess the effect of reward on demand ratings and RTs, we included the maximum reward on offer (i.e., max of all four outcomes across options) Z-scored within-person as well as the interaction between reward and demand level. We also assessed the effect of task difficulty on log-transformed response times and EV maximizing choice. For the choice model, we estimated the effect of difficulty using a logistic mixed-effects regression predicting the binary outcome of choice (0=non-maximizing, 1=maximizing). For all regressions, we also included a per-participant random intercept and a random slope of task difficulty.

Results

Figure 2.

Behavioural results for all three experiments. The dots and lines represent individual participants in each study. **A**. Participants were also slower at responding when deciding between difficult choices when compared to easy choices across all experiments **B** Participants were more likely to select the Expected Value (EV) maximizing option for the easy over the difficult choices across all experiments.

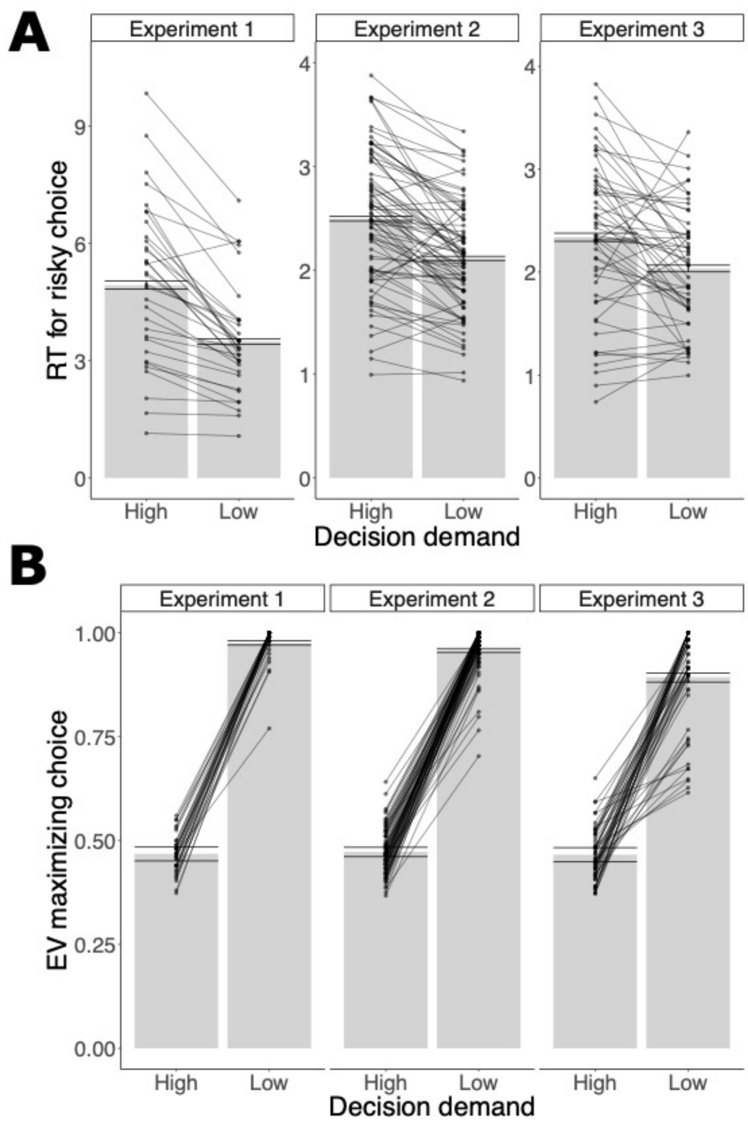


Table 1.

Results of the hierarchical linear regression on demand ratings as a function of choice difficulty, trial-level max reward on offer Z-scored within person, and trial-level RT Z-scored within person and difficulty, their interaction, as well as the covariates of stimulus color and run order.

Predictors	Estimates	CI	p
(Intercept)	2.22	1.96 – 2.48	<0.001
Choice Difficulty (Easy vs. hard)	1.56	1.20 – 1.91	<0.001
RT (Z score)	0.48	0.28 – 0.68	<0.001
Reward on Offer (Z Score)	-0.02	-0.08 – 0.04	0.481
Color (Red vs Blue)	-0.05	-0.13 – 0.03	0.185
Run Order (2 vs 1)	0.12	-0.33 – 0.58	0.590
Run Order (3 vs 1)	-0.26	-0.69 – 0.17	0.241
Run Order (4 vs 1)	0.02	-0.44 – 0.48	0.941
Difficulty * RTZ	0.20	0.03 – 0.36	0.021
Difficulty * Reward	0.18	0.10 – 0.26	<0.001

Subjective Ratings

We first assessed whether our manipulation of choice difficulty engendered changes in subjective ratings of confidence and demand. As depicted in Figure 2B, participants rated the more difficult choices (M_{Hard}= 3.88) as more demanding than the easier choices (M_{Easy}= 2.09). We confirmed this result statistically with our hierarchical linear regression which revealed a statistically significant main effect of choice difficulty (b= 1.56, 95%CI= [1.20, 1.91], p<0.001; see Table 1). Again, we assessed whether response times on the risky choice predicted subsequent demand ratings and found a significant positive relationship (b= 0.48, 95%CI= [0.28, 0.68], p<0.001; see Table 1). This result suggests that taking longer to decide was associated with higher demand ratings. The results of our regression also revealed a significant positive interaction between choice difficulty and RTs (b= 0.20, 95%CI= [0.03, 0.36], p<0.001). This suggests that for difficult choices, response slowing has a larger impact on subjective feelings of demand. In terms of rewards, there was no relationship between the chance to win a larger reward on demand ratings for the easy choices (b= -0.02, 95%CI= [-0.08, 0.04], p= .481; see Table 4). Yet, the opportunity to win a larger reward led to higher demand ratings for the difficult choices (b= 0.18, 95%CI= [0.10, 0.26], p< .001; see Table 1). Together these results suggest that much like the decision to exert cognitive control, effort investment in value-based choice similarly follows a Cost-Benefit tradeoff: rewards offset the costs of effort investment associated with demanding choices and lead to faster choices which are rated as more demanding.

Table 2.

Results of the hierarchical linear regression on confidence ratings as a function of choice difficulty, trial-level max reward on offer Z-scored within-person, trial-level RT Z-scored within-person and difficulty, their interaction, as well as the covariates of stimulus color and run order.

Predictors	Estimates	CI	p
(Intercept)	6.07	5.81 – 6.33	<0.001
Choice Difficulty (Easy vs. hard)	-1.50	-1.71 – -1.29	<0.001
RT (Z score)	-0.18	-0.38 – 0.02	0.076
Reward on Offer (Z Score)	0.09	0.03 – 0.15	0.002
Color (Red vs Blue)	-0.00	-0.08 – 0.08	0.944
Run Order (2 vs 1)	-0.05	-0.50 – 0.41	0.842
Run Order (3 vs 1)	0.16	-0.28 – 0.59	0.480
Run Order (4 vs 1)	0.01	-0.44 – 0.47	0.957
Difficulty * RTZ	-0.27	-0.43 – -0.11	0.001
Difficulty * Reward	-0.11	-0.19 – -0.03	0.006

In terms of subjective confidence, participants felt less confident in having made the best choice when deciding between the difficult options (M_{Hard}= 4.52) when compared to the easy options (M_{Easy}= 6.11; see Figure 2B). We confirmed this effect statistically with our hierarchical linear regression which revealed a statistically significant main effect of choice difficulty (b= -1.50, 95%CI= [-1.71, -1.29], p< .001; see Table 2). We also assessed whether decision times—Z-scored within-person and choice difficulty—predicted confidence ratings and failed to find a significant relationship (b= -0.18, 95%CI= [-0.386, 0.02], p=.076; see Table 2). Importantly, choice difficulty was found to moderate the relationship between decision times and confidence. The results of our regression also revealed a significant negative interaction between choice difficulty and z-scored RT suggesting that the negative relationship between RT and confidence is stronger for difficult choices (b= -0.27, 95%CI = [-0.43, -0.11], p=.001; see Table 2). Participants felt more confident when there was a chance to win a larger amount of money (b= 0.09, 95%CI= [0.03, 0.15], p=.002; see Table 2) but this relationship was attenuated for the difficult choices as indexed by a difficulty reward interaction (b= -0.11, 95%CI= [-0.19, -0.03], p=.006; see Table 2). Together, our results suggest that difficult choices reduce both confidence and the benefits of reward prospects on confidence, as well as increase the sensitivity to response times when rating confidence.

Performance

Next, we assessed whether our manipulation of choice difficulty engendered a change in behavioural performance namely on response times and EV maximizing choice. As depicted in Figure 2A, participants were slower at responding to the difficult choices (M_{Hard}= 5.02 seconds) when compared to the easy choices (M_{Easy}= 3.57 seconds). This slowing was confirmed statistically by the main effect of trial type in our hierarchical linear regression on log response-times (b = 0.33, 95% CI = [0.26, 0.40], p < .001; see Table 3). We also observed a significant decrease in EV maximizing choice for the hard choices (M_{Hard}= 47%) when compared to easy choices (M_{Easy}= 95%; see Figure 2B), suggesting our manipulation of discriminability worked. The results of our hierarchical logistic regression confirmed this decrease in EV maximizing choice (b= -3.84, 95% CI= [-4.08, -3.61], p < .001; see Table 4). Together, these results suggest that our stimuli successfully manipulated choice difficulty as demonstrated by slower response times and less sensitivity to expected values.

Table 3.

Results of the hierarchical linear regression on log-transformed response times as a function of choice difficulty, trial-level max reward on offer Z-scored within-person, as well as the covariates of stimulus colour and run order.

Predictors	Estimates	CI	p
(Intercept)	1.10	0.96 – 1.23	<0.001
Choice Difficulty (Easy vs. hard)	0.33	0.26 – 0.40	<0.001
Reward on Offer (Z Score)	0.02	0.01 – 0.04	0.001
Color (Red vs Blue)	0.00	-0.02 – 0.02	0.798
Run Order (2 vs 1)	0.17	-0.07 – 0.40	0.169
Run Order (3 vs 1)	0.10	-0.13 – 0.33	0.406
Run Order (4 vs 1)	-0.27	-0.51 – -0.03	0.025
Difficulty * Reward	-0.05	-0.07 – -0.03	<0.001

Table 4.

Results of the hierarchical logistic regression on EV maximizing choice as a function of choice difficulty, trial-level max reward on offer Z-scored within-person as well as the covariates of stimulus colour and run order.

Predictors	Log-Odds	CI	p
(Intercept)	3.71	3.48 – 3.94	<0.001
Choice Difficulty (Easy vs. hard)	-3.84	-4.08 – -3.61	<0.001
Reward on Offer (Z Score)	0.05	-0.18 – 0.28	0.697
Color (Red vs Blue)	0.05	-0.08 – 0.18	0.472
Run Order (2 vs 1)	0.01	-0.14 – 0.16	0.896
Run Order (3 vs 1)	0.06	-0.08 – 0.20	0.421
Run Order (4 vs 1)	-0.04	-0.19 – 0.11	0.600
Difficulty * Reward	-0.02	-0.26 – 0.22	0.880

Next, aligned with the predictions of Cost-Benefit models of effort allocation, we assessed whether the importance of the decision (i.e., high-stakes decisions) affected choices and response times. We tested whether participants responded more quickly when there was the potential to gain greater rewards (Shevlin et al., 2022)—indexed here as the maximum of all outcomes of both risky options—and found that the potential to gain larger rewards was associated with slower responses for easy choices ($b= 0.02$, 95%CI= [0.01, 0.04], $p< .002$; see Table 3). Yet, for difficult choices, the potential to gain greater rewards was associated with faster responses as shown by the significant interaction between maximal reward and trial difficulty ($b = -0.05$, 95%CI = [-0.07, -0.03], $p < .001$, see Table 3). However, we failed to find any modulation of EV sensitivity to rewards on offer for both easy ($b= 0.05$, 95%CI= [-0.18, 0.28], $p =.697$; see Table 4) and difficult choices ($b= -0.02$, 95%CI= [-0.26, 0.22], $p= .880$; see

Table 4). Together these results provide preliminary evidence that the effort invested in deliberating between choices is modulated by both choice difficulty and rewards.

Discussion

Can value-based choice task demands be experimentally manipulated? Previous work has used the discriminability of the options' Expected value to manipulate task demands (da Silva Castanheira, Fleming, et al., 2021; De Martino et al., 2013; Lebreton et al., 2009; Lee & Daunizeau, 2021; Zysset et al., 2006). Yet these manipulations rely on the assumption that participants are using differences in EV to decide, which may not always be the case (Coombs et al., 1970). Alternatively, other work has used the *Strategic conflict*—the conflict between different decision strategies—to manipulate task demands (Venkatraman et al., 2009). Recent work has extended this notion by suggesting cognitive control—the selection of relevant responses to value-based decision-making—is used to select responses congruent with one's goals (Frömer & Shenhav, 2021).

The results of the first experiment demonstrated that choices low in discriminability and high strategic conflict are experienced as demanding, both in terms of demand ratings and performance. While it remains unclear what specifically, makes a value-based choice demanding, we show that these task demands can be systematically and reliably manipulated. Leveraging the previous choice set and extant work on cognitive control demonstrating demand avoidance (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010; McGuire & Botvinick, 2010; Vogel et al., 2020; Westbrook & Braver, 2015), we sought to test a central prediction of the Cost-Benefit Model of effort: effort should be avoided all else being equal (i.e., rewards on offer).

Section 4.3: Experiment 2

The goal of the current experiment was to test whether demanding value-based choices are avoided in favour of less demanding value-based choices. To this end, we asked participants to complete the decision avoidance task (DAT) where they first learned the association between stimuli and their resulting decisions; and then were asked to freely choose between the stimuli. The DAT was modelled after previous work which investigated the avoidance of cognitive control exertion using a task called the *demand selection task* (Kool et al., 2010).

Method

Participants

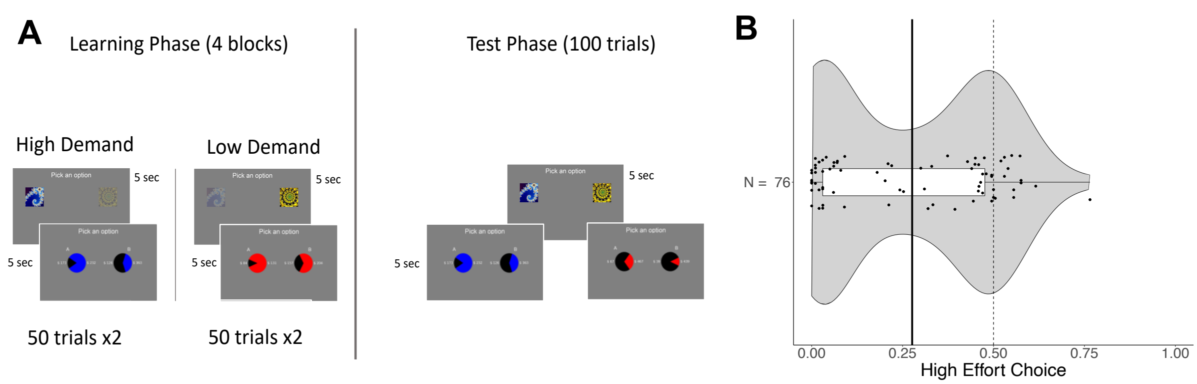
Data were collected from 81 participants recruited via the McGill University's Psychology participant pool (20 males; 18-33 years old; Mean= 21.17; SD= 2.81). We excluded data from two participants as it failed to record properly. To ensure participants understood the task we further excluded the data of one participant who failed to pick the EV maximizing choice on more than 60% trials for the easy stimuli during the learning phase. This resulted in the exclusion of 5 participants.

Materials and Procedures

First, participants completed the digit-symbol coding task (Kail & Salthouse, 1994; Mathias et al., 2017; da Silva Castanheira, Sharp, et al., 2021), followed by the Operation Span task (Unsworth et al., 2005; Unsworth & Engle, 2005). Next, participants were asked to complete the *Decision Avoidance Task* followed by a Framing Effect task. The choice sets were identical to the first experiment. Because we did not want to introduce demand characteristics to the DAT, by highlighting the main difference between the choice sets was demand level, we opted not to collect subjective ratings for this study. After completing the DAT, participants completed a Framing Effect task and several questionnaires in a counterbalanced order (i.e., maximization, Need for cognition, and State-Trait Anxiety Inventory). Please refer to the Supplemental Materials for details.

Figure 3.

A Schematic depicting the decision avoidance task (DAT). In the learning phase, participants were asked to learn the kinds of choices each stimulus (i.e., fractal) was associated with. Choices were offered between two risky options for whose outcomes and associated probabilities were depicted as pie charts. In the Test phase, participants were told to choose the stimulus associated with the set of choices they preferred. **B** Violin plot with an embedded boxplot depicting proportion High effort choice during the test phase for the 76 participants. The dashed line represents chance (0.5) and the solid black line represents the median high effort choice proportion (0.27).



Decision Avoidance Task

To test whether high-demand choices are avoided we asked participants to complete a demand selection task where participants learned the association between stimuli and decisions and then were instructed to select the stimulus they preferred (Kool et al., 2010). In the task, two fractals (randomly selected without replacement from a set of 4 possible fractals) were each associated with a set of risky decisions. Critically, one stimulus was always associated with decisions from the easy set of choices outlined in Experiment 1 while the other was associated with the hard choices outlined in Experiment 1. The decision type and stimulus association were counterbalanced across participants (see Figure 3). Critically, participants were not instructed of this key difference in demand level. Instead, they were simply instructed to select the "patterned image" (stimulus) associated with the decisions they preferred. This task consisted of two phases separated by a self-paced break. In the first phase (Learning phase) participants were asked to learn the association between the stimuli and the associated choice sets. To learn the association, presented participants with a forced choice of stimulus by increasing the transparency of one of the stimuli and forcing participants to select the opaque stimulus. Participants were presented 50 consecutive trials for each stimulus before alternating to the other stimulus in a counterbalanced order. Then, participants completed the test phase where they were able to freely choose between the two stimuli for a total of 100 trials. Across both phases, participants had 5 seconds to choose for both the fractal and risky choices (see Figure 8). Of interest, we measured participants' choice of fractal (high vs low demand) during the test phase.

Data Analysis

We assessed the effect of task difficulty on log-transformed decision times between the risky options, and EV maximizing choice using a linear mixed-effects regression and a logistic mixed-effects regression predicting the binary outcome of choice (0=non-maximizing, 1=maximizing) respectively. For these two models, we only used choices from the learning phase as there were equal number of observations for each decision type (hard versus easy). Next, we assessed whether participants avoided demanding decisions by estimating a hierarchical logistic regression predicting high demand choice during the test phase. Critically, we tested whether the group intercept of the model, reflecting general choice preference, was different from chance—indicating a reliable preference for either low or high-demand decisions.

Results

Replication of Demand Manipulation

Table 5.

Results of the hierarchical linear regression on log Response-times during the learning phase as a function of stimulus type (Hard vs. Easy) and trial-level total reward on offer Z-scored within-person.

Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.67	0.61 – 0.73	<0.001
Choice Demand (Hard vs. Easy)	0.16	0.11 – 0.20	<0.001
Reward on Offer (Z Score)	0.02	0.02 – 0.03	<0.001
*Demand * Reward*	-0.04	-0.05 – -0.03	<0.001

Table 6.

Results of the hierarchical logistic regression on EV maximizing choice during the learning phase as a function of stimulus type (Hard vs. Easy) and trial-level total reward on offer Z-scored within-person.

Predictors	Log-Odds	CI	p
(Intercept)	3.27	3.08 – 3.47	<0.001
Choice Demand (Hard vs. Easy)	-3.39	-3.58 – -3.19	<0.001
Reward on Offer (Z Score)	-0.09	-0.20 – 0.03	0.136
Demand * Reward	0.10	-0.03 – 0.22	0.122

We first attempted to replicate the performance results in Experiment 1: longer decision times and lower choice consistency (i.e., EV maximizing choice) for the high-demand choices.

Consistent with our previous experiment, participants were significantly slower on difficult compared to easy decisions ($b= 0.16$, 95%CI= [0.11, 0.20], $p < .001$; See Table 5 and Figure 2A). Next, replicating our previous experiment, we found people were less consistent at picking the EV maximizing choice for the difficult decisions ($b= -3.39$, 95%CI= [-3.58, -3.19], $p < .001$; See Figure 2B and Table 2). Again, we failed to find evidence that total reward on offer motivated EV maximizing choice ($b= -0.09$, 95%CI= [-0.20, 0.03], $p= .164$; See Table 6) nor was it dependent on decision demand ($b= 0.10$; 95%CI = [-0.03, 0.22], $p= .122$; see Table 6). We also found that participants were slower when the stakes were higher ($b= 0.02$, 95%CI= [0.02, 0.03], $p < .001$; See Table 5) but that decision difficulty modulated the effect of rewards on response times ($b= -0.04$, 95%CI= [-0.05, -0.03], $p < .001$; See Table 5). In other words, participants were faster when the maximum reward on offer was larger, but only for difficult decisions.

Demand Avoidance

Table 7.

Results of the hierarchical logistic regression on high demand choice during the test phase as a function of trial, counterbalance condition and individual differences in decision-frame susceptibility, Processing speed (z-scored), Maximization (z-scored), Need for cognition (z-scored), and Operation span (z-scored).

Predictors	*Log-Odds*	*CI*	*p*
(Intercept)	*-1.41*	*-2.02 – -0.80*	*<0.001*
Framing Effect	*-0.30*	*-0.59 – -0.02*	*0.039*
Digit Symbol score	*-0.01*	*-0.04 – 0.02*	*0.421*
Maximization	*-0.33*	*-0.78 – 0.12*	*0.155*
Need for Cognition	*-0.19*	*-0.65 – 0.26*	*0.405*
OSPAN	*-0.13*	*-0.61 – 0.35*	*0.592*
Trial	*0.03*	*-0.07 – 0.13*	*0.598*
Counterbalance	*0.31*	*-0.57 – 1.19*	*0.490*

Our main question for this experiment was whether people consistently avoid difficult decisions in the test phase. Of interest, we wanted to see if people would reliably choose the fractal associated with the easier decisions, as indexed by a negative intercept in our hierarchical logistic regression predicting high demand choice. As depicted in Figure 3B, we found that participants reliably avoided the difficult decisions (Median proportion high demand choice = 0.27); this was confirmed statistically by a negative intercept in our hierarchical logistic regression (b= -1.41, 95%CI= [-2.02, -0.80], p<.001).; see Table 7). Thus, participants were more likely to select the low demand choices, beyond chance level.

Individual differences as predictors of Demand Avoidance

Next, we tested whether individual differences in motivation, or cognitive ability or predicted demand avoidance in the DAT. To this end, we modelled high-demand choice in the test phase as a function of trial, counterbalance condition, Processing speed, Maximization, Need for cognition, and Operation span. Critically, our measures of individual differences were not strongly correlated to each other (all r's < 0.30) Our results suggest that neither measure of cognitive ability (i.e., processing speed or operation span) was a significant predictor of high-demand choice (both p > .40). We also failed to find a relationship between effort avoidance and either individual motivation to engage in effortful tasks as indexed by the need for cognition or individual tendency to decide without much cogitation as indexed by scores on the maximizer scale (both p >. 15). Together, our results suggest that the effort avoidance observed could not be better explained by a lack of motivation or cognitive ability.

Discussion

All else being equal, people should avoid demanding cognitive tasks (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2013, 2017), a behaviour which has been consistently found in the cognitive control literature (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010; McGuire & Botvinick, 2010; Vogel et al., 2020; Westbrook & Braver, 2015). The results of the previous experiment extend these findings to demonstrate that demanding risky choices are also avoided, all else being equal. Together, these results tentatively suggest that participants are avoiding demanding risky choices due to the increased effort costs associated with deliberation.

Section 4.4: Experiment 3

Previous work has established task-evoked pupillary responses (i.e., TEPRs) as a viable index of momentary effort exertion in cognitive control tasks (da Silva Castanheira, LoParco, et al., 2021; van der Wel & van Steenbergen, 2018). Yet, whether pupillary responses can index effort investment in risky decision-making remains unclear as it can also track other factors (Bray et al., 2008; Eldar et al., 2021; Lavín et al., 2014; J. P. O'Doherty et al., 2003; Preuschoff et al., 2011; Van Slooten et al., 2018). In this experiment, we will leverage measures of pupillary dilation to test whether greater demand avoidance can, in part, be explained by greater effort costs. Thus, this experiment is twofold: 1) test whether trial-by-trial pupil dilations increase in response to greater decision demands and 2) test whether individual differences in pupil dilation predict future demand avoidance in value-based choice. We hypothesize that high-demand choices will elicit greater effort investment thereby increasing pupil diameter and that greater effort investment—indexed by larger pupillary responses—will predict greater demand avoidance.

Method

Participants

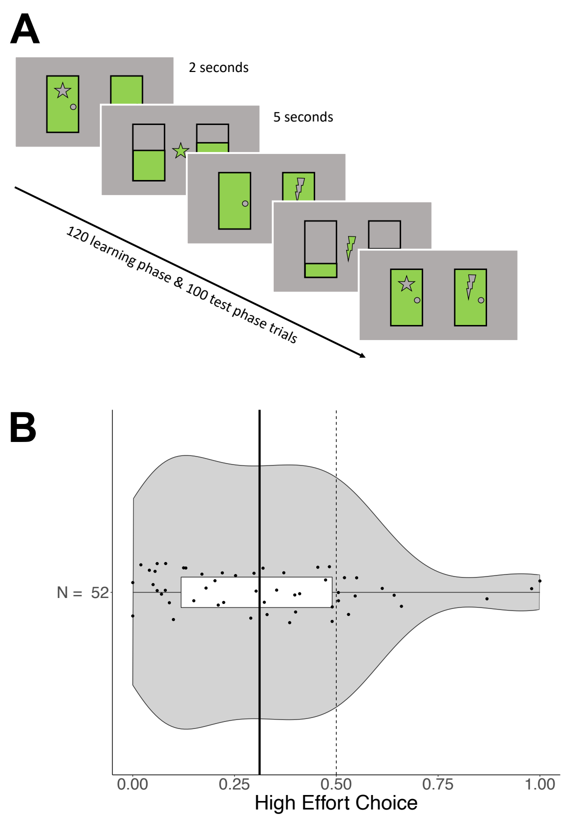
We collected data from 81 English-speaking participants (18 males, 2 non-binary participants, 18 – 29, M_{age}= 20.99, SD=2.44) recruited from the McGill University community for a base remuneration of $20 CAN or 2 class credits and a performance-contingent cash bonus of up to $5. All participants were screened for corrected-to-normal, colour blindness, and diagnoses of psychiatric or neurological conditions. We excluded those participants who failed 40% or more of the catch trials, those who failed to respond to more than 20% of trials, or those without reliable pupil recordings based on visual inspection of the eye data .With these exclusion criteria, 29 participants were excluded from the analysis resulting in a final sample of 52.

Materials and Procedures

Participants were seated comfortably in front of a 24-inch monitor set to a resolution of 1280x1024 pixels in a dimly lit room and instructed to keep their heads rested on a mount positioned 60 centimetres away from the screen. During both the demand selection task and the risky decision-making task, participants' left pupil diameter was measured using an Eyelink-1000 eye tracker (SR Research, Osgoode, ON) at a sampling rate of 250 Hz. Prior to the start of each experimental block, participants underwent a nine-point calibration procedure.

Figure 4.

A Schematic of the Decision Avoidance task adapted for pupillometry. **B** Violin plot of high demand choices in the test phase of the DAT.

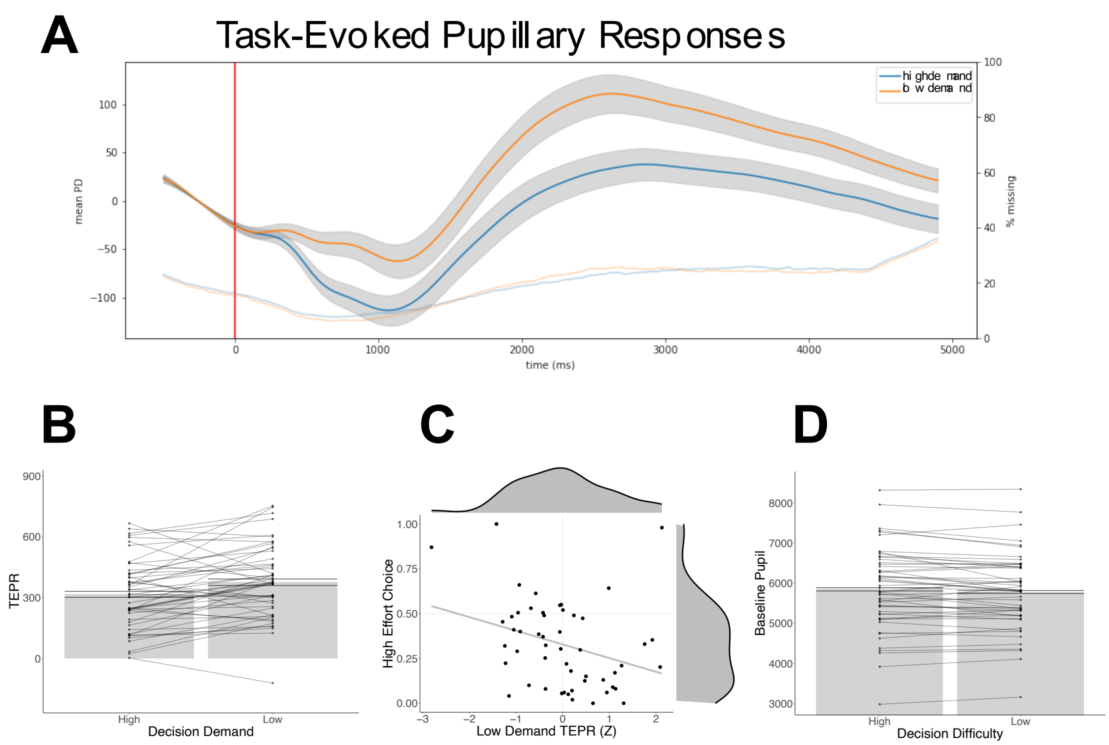


Decision Avoidance Task

Following the procedures of Experiment 2, participants were be asked to complete a Decision Avoidance Task. To control for possible differences in luminance which could confound our pupil measure (Joshi & Gold, 2020), we ensured that both stimuli were as visually similar as possible and thus opted to use two similar coloured rectangles each with an identifying symbol (i.e., a five-point star or lightning bolt; see Figure 4A). Participants had two seconds to decide between the two doors using the keyboard, and trials were not response terminated but instead masked until 2 seconds have elapsed. After selecting the desired door, participants were shown a choice between two gambles, now presented as stacked bar charts (Tymula et al., 2012). These bar charts depicted the probability of each outcome as the height of the bar, with the associated reward amount written on the screen. We chose bar charts as this would minimize changes in the overall luminance and appearance of the screen between the cues and stimuli. Critically, trials were not response-terminated but instead had a fixed duration of 5 seconds with a visual mask applied after responding. After which, participants were presented a fixation cross which served as a jittered inter-trial interval between 2.5 to 3.5 seconds. To complete the task within the 2-hour experimental session, and to avoid fatigue, we reduced the total number of trials from 200 (50 each block) in Experiment 2 to 120 in the learning phase (30 each block). Trials were organized into 4 learning phase blocks and 2 test phase blocks.

Figure 5.

A Graph of group-level task-evoked pupillary responses in the learning phase as a function of high (blue) and low demand (orange) choices. **B** Participants' TEPRs were significantly smaller for the high- compared to the low-demand decisions. **C** Scatterplot with marginal distributions of low-demand TEPRs in the learning phase and high effort choice in the test phase. **D** Participants' baseline pupil diameter was significantly higher in high-demand blocks compared to low-demand blocks.



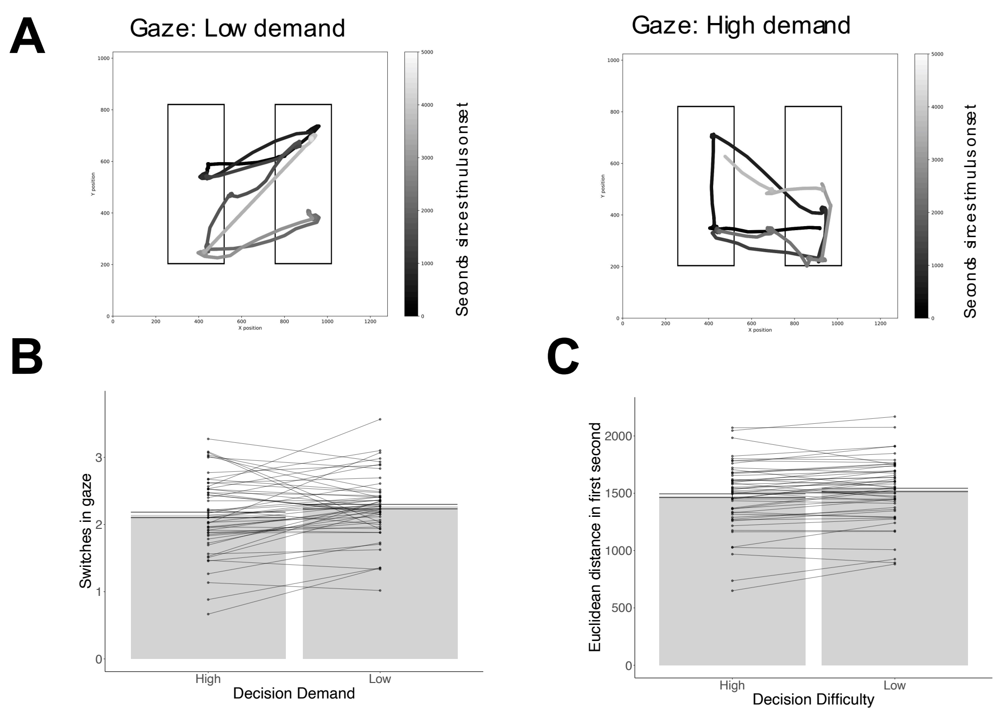
Pupillary Data Analysis

Pupillary data were preprocessed before computing trial-by-trial task-evoked pupillary responses (TEPRs) using the pypillometry python package (Mittner, 2020). Eye blinks were corrected using linear interpolation and passed through a low-pass filter to high-frequency noise above a frequency of 1 Hz. Pupillary data were baseline-corrected on a trial-by-trial basis by subtracting the mean diameter of a 500ms baseline period prior to stimulus presentation. TEPRs will be calculated as the maximum pupil diameter (da Silva Castanheira, LoParco, et al., 2021; Gilzenrat et al., 2010) observed between 1000ms and 3000ms after stimulus onset while deciding between the two risky options. This time window of interest corresponds approximately to the median response time for the learning phase of the decision avoidance task in the previous experiment (RT_{Hard}= 2.40, RT_{Easy}= 1.96).

We compared pupil diameter across trial types (i.e., Hard vs Easy) to test whether pupil diameter is sensitive to the manipulations of strategic conflict. To this end, we used a hierarchical linear regression predicting TEPRs as a function of demand level controlling for trial number, the maximum reward on offer, the outcome probabilities of the left and right options, and whether and EV maximizing choice was made. Importantly, we included a random per-participant slope for demand level in the regression model. Using these individual estimates of demand on pupillary dilation, we will then predict demand avoidance in the test phase as a function of pupillary differentiation.

Figure 6.

A Example gaze trajectory from a participant for a low- and a high-demand trial. **B** Participants switched their gaze between the two options less often for the high-demand choices when compared to the low-demand choices. Bar plot of the average number of switches as a function of decision demand. **C** Participants looked at more areas on the screen in the first second of the trial for the low-demand choices when compared to the high-demand choices. Bar plot of average Euclidean distance in the first second as a function of decision demand.



Eye Movement Data Analysis

Using the eye-tracker, we measured eye-movements between the presentation of the gamble stimulus and participants' response. Like with the pupillary data, the eye-position data i.e., x and y pixel coordinates were blink-corrected using linear interpolation and down-sampled to a frequency of 100Hz. We defined large two areas of interest (AOI) centered on the gamble options presented to the participant, with a slack of 100 pixels to the left and right of the gambles, running the entire height of the screen (see Figure 6A). Using these two AOIs, we computed the total number of shifts in gaze between these two areas before responding (Folke et al., 2016). We also wanted to assess the amount of information sampling in a trial aligned with previous work in multi-attribute decision-making (Wedel et al., 2022; Yang et al., 2018; Yegoryan et al., 2020). However, the current risky decision-making task did use not the typical use a gaze-contingent drawing paradigm for multi-attribute choice as this would affect our ability to control the overall luminance and accurately measure pupil diameter. Thus, we are unable to measure the number of fixations for each individual attribute (i.e., probability versus outcome) and instead opted for change in gaze position as is typical for visual search tasks (Stephen & Anastas, 2011). We computed the sum of total Euclidean distance (in pixels) covered by the eye movements in the first second of the trial.

Again, we compared both the number of switches and the total distance covered between high and low-demand trials in the learning phase using hierarchical regressions. We used a hierarchical Poisson regression to predict the total number of switches on a given trial from the demand level controlling for trial number, the total reward on offer, the outcome probabilities of the left and right options, and whether an EV maximizing choice was made. The total distance covered was also modelled using a linear regression with the same predictors.

Behavioural Data Analysis

As with the first two Experiments, we used hierarchical regressions to predict log response times and EV maximizing choice during the learning phase as a function of demand (high versus low) and total reward on offer. Additionally, we modelled demand avoidance as a function of median pupil dilation in the learning phase for high- and low-demand choices.

Results

Behavioural Results

First, we tested whether we observed a similar behavioural profile to the choices given the new visual presentation of the gambles. Our hierarchical linear regression on log RTs confirmed that participants were slower on high demand compared to low demand trials (b= 0.11, 95% CI= [0.04, 0.18], p=0.001; See Figure 2A and Table 8). Similarly, we replicated both the main (b= 0.02, 95%CI = [0.00, 0.03], p=0.013) and interaction between choice demand level and total reward on offer (b= -0.04, 95%CI= [-0.06, -0.02], p<0.001; Table 8) suggesting that participants sped up when both the total reward at stake the task demand were high. Once again, we found that participants were also worse at selecting the EV maximizing option for the high-demand trials when compared to the low-demand trials (b= -3.010, 95%CI= [-3.64, -2.55], p<0.001, see Figure 2B and Table 9). Importantly, we again find evidence for demand avoidance in the test phase of the decision avoidance task as evidenced by the intercept of the logistic hierarchical regression predicting high demand choice (b= -0.98, 95%CI= [-1.41, -0.54], p<0.001; see Figure 4B). Together, these results replicate the behavioural findings from experiments 1 and 2, suggesting generalization across different stimulus presentations.

Table 8.

Results of the hierarchical linear regression on log Response-times during the learning phase as a function of stimulus type (Hard vs. Easy) and trial-level total reward on offer Z-scored within-person.

Predictors	Estimates	CI	p
(Intercept)	0.61	0.52 – 0.70	<0.001
Choice Demand (Hard vs. Easy)	0.12	0.05 – 0.19	0.001
Reward on Offer (Z Score)	0.02	0.00 – 0.03	0.013
Trial	-0.05	-0.07 – -0.04	<0.001
Demand * Reward	-0.06	-0.08 – -0.04	<0.001

Table 9.

Results of the hierarchical logistic regression on EV maximizing choice during the learning phase as a function of stimulus type (Hard vs. Easy) and trial-level total reward on offer Z-scored within-person.

Predictors	Log-Odds	CI	p
(Intercept)	3.37	2.74 – 3.99	<0.001
Choice Demand (Hard vs. Easy)	-3.10	-3.64 – -2.55	<0.001
Reward on Offer (Z Score)	0.07	-0.08 – 0.21	0.371
Trial	-0.10	-0.27 – 0.08	0.275
Demand * Reward	-0.01	-0.18 – 0.17	0.951

Pupillary Results

Next, we assessed whether choice demand level impacted participant's task-evoked pupillary response (TEPRs) when deciding between gambles in the learning phase of the task. To this end, we compared participants' maximum, baseline-corrected, pupil dilation 1 to 3 seconds after stimulus presentation between demand conditions. The linear mixed-effects regression revealed a significant difference in pupil size between choice types, such that low-demand choices were associated with higher pupil dilations ($b= -61.46$, 95%CI= [-93.62, -29.31], $p<0.001$; see Figure 5B). Next, we assessed whether pupil diameter for low-demand trials was comparable between the learning and test phases of the task but failed to find a difference ($b= 38.60$, 95%CI= [-85.62, 8.42], $p=0.108$). Finally, we tested whether median high- and low-demand TEPRs during the learning phase could predict demand avoidance in the test phase. We found that larger pupil diameter for low ($b= -0.68$, 95%CI= [-1.33, -0.03], $p= 0.042$; see Table 10 and Figure 5C) but not high-demand trials predicted fewer high-demand choices ($b= 0.25$, 95%CI= [-0.40, 0.90], $p= 0.444$; see Table 10). Together with the behavioural and eye movement results, our pupillary analyses suggest that participants were withdrawing effort exertion during high-demand choices in the learning phase, and this degree of effort withdrawal predicts demand avoidance in the subsequent task phase.

Table 10.

Results of the hierarchical logistic regression on high demand choice during the test phase as a function of trial, and individual differences in median TEPRS for the high and low demand choices in the test phase.

Predictors	Log-Odds	CI	p
(Intercept)	-0.98	-1.41 – -0.54	<0.001
Trial	0.00	-0.11 – 0.12	0.954
High demand TEPR	0.25	-0.40 – 0.90	0.444
Low demand TEPR	-0.68	-1.33 – -0.03	0.042

We further probed whether participants were withdrawing their effort by testing whether high-demand blocks had higher tonic pupil diameter indexed here by the average pupil diameter in the 500ms baseline period prior to stimulus onset. Tonic pupil diameter has previously been used as a measure of task disengagement as it is thought to reflect tonic levels of norepinephrine in the Locus Coeruleus (Aston-Jones & Cohen, 2005; Gilzenrat et al., 2010; Rajkowski et al., 1994). The results of our linear hierarchical regression reveal that participants' tonic pupil size was significantly higher during high-demand blocks in the learning phase controlling for presentation order ($b= 90.90$, 95%CI= [44.86, 136.94], $p<0.001$; see Figure 5D).

Eye Movement Results

Next, we assessed whether there was any evidence for different patterns of gaze between the high- and low-demand stimuli, suggesting a difference in effort investment. First, we ensured our measure of fixation captured fixations at the stimuli by comparing total percent fixation in our areas of interest. We find that overall, participants overwhelmingly spent their time looking at either of the two stimuli ($b= 0.98$, 95%CI= [0.98, 0.99], $p<0.001$) and the demand level was not found to affect fixations to the stimulus (b= 0.00, 95%CI= [-0.00, 0.00], p= 0.809). Second, we tested whether participants switched between looking at the stimuli more often in the high- compared to the low-demand condition. To do so, we modeled the number of switches using a hierarchical Poisson regression as a function of choice demand level. Surprisingly, we found that participants switched their gaze between the two stimuli less often for the high compared to the low-demand choices (b= -0.06, 95%CI= [-0.12, -0.01], p=0.031; see Supplementary Table S4 and Figure 6B). We also found that the difference in number of switches between low and high demand choices (i.e., Δ switch (low – high)) was larger for when the stakes were also higher as indicated by a reward on offer by demand level interaction (b = -0.05, 95%CI= [-0.09, -0.02], p = .004; see Supplementary Table S4). Finally, we assessed whether the distance covered by the participants' gaze in the first second of the trial and their average speed of fixations differed between choice demand level. Modelling total Euclidean distanced covered in the first second, we found participants' gaze covered less area on the screen in the first second of the trial for high- compared to low-demand trials (b= -40.55, 95%CI= [-67.31, -14.39], p<0.001; see Supplementary Table S5). Again, we found that total rewards on offer increased the difference in information sampling between high- and low-demand choices for the total distance covered in the first second (b= -19.61, 95%CI= [-37.52, -1.69], p= 0.032). Importantly, we failed to find any difference between the number of switches (b= -0.019, 95%CI= [0.03503, -0.536], p=0.591), and the total distance covered in the first second (b= 21.55, 95%CI= [-16.14, 59.23], p=0.262) between the test and learning phase for low-demand choices.

We also tested whether distance covered in the first second, z-scored within demand level, predicted whether participants made and EV maximizing choice. We found that participants were more likely to make an EV maximizing choice as they sampled more information (b= 0.44, 95%CI= [0.27, 0.60], $p < 0.001$; see Supplementary Table S6). However, the relationship between fixation speed and EV maximizing choices was only true for low-demand choices (b= -0.41, 95%CI= [-0.60, -0.322], $p< 0.001$; see Supplementary Table S6). Together, our eye fixation data suggest that participants are seeking out less information for the high-demand choices.

Section 4.5: General Discussion

Across three experiments, we demonstrate that task demands of value-based choices can be systematically and reliably manipulated both in terms of subjective reports and behaviourally in terms of response slowing. We also demonstrate that people tend to avoid these decisions where there is greater strategic control. Together, our results are aligned with previous work in the cognitive control literature which suggests that humans avoid tasks high in cognitive demands all else being equal (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010; McGuire & Botvinick, 2010; Westbrook & Braver, 2015)—and will even opt for a painful stimulus over the prospect of exerting cognitive effort (Vogel et al., 2020). Despite these results, participants' pupil dilations, a marker of momentary effort exertion (da Silva Castanheira, LoParco, et al., 2021), were surprisingly larger for low- compared to high-demand choices. While it appears behaviourally choices with high strategic control are more effortful, physiologically these choices elicited less effort investment. Below, we discuss a possible interpretation of these purportedly conflicting findings.

Cost-benefit models of effort investment suggest that individuals will exert themselves when the benefits outweigh the costs (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018). This model suggests that effort investment should increase as a function of task demands, all else being equal. However, as the task demands and costs of effort increase, the effort invested should decrease (Silvestrini et al., 2022; Brehm & Self, 1989). This suggests the relationship between task demands and effort investment can be characterized by an inverted-U: as task demands increase, effort investment increases up to a critical point, after which people will begin to disengage (Silvestrini et al., 2022). We believe the discrepancy between the behavioural and physiological data can be explained by the disengagement of effort in response to excessive task demands. Firstly, we find that participants' pupil diameter reflected the typical pattern of task disengagement: low task-evoked pupillary responses and high baseline pupil dilation (da Silva Castanheira, LoParco, et al., 2021). Other work has similarly found higher baseline pupil diameter during high-demand cognitive control tasks (McGuire & Botvinick, 2010). This pattern of pupillary responses is thought to reflect the functioning of the Locus-Coerleus norepinephrine functioning which is important for specifying the control state: where high tonic but low phasic functioning reflects disengagement from the current task to explore new ones (Gilzenrat et al., 2010). Secondly, we show that individual differences in effort exertion predict the degree of decision avoidance: those who invest the most effort in low-demand choices, indexed by their pupil dilations are those who are most demand-avoidant. In other words, those who invested the least amount of effort in the low-demand trials showed a near-chance preference for the high-demand option, either reflecting a failure to learn the stimulus-demand contingency or indifference. Our results suggest that this avoidance of effort reflects the inherent costs of cognitive effort (Kurzban et al., 2013). Alternatively, the observed pattern of larger pupil dilation to the low-demand choices may also reflect some other factors like individual preferences (Hess & Polt, 1960). However, we believe this is unlikely as participants' pattern of fixations suggested differential investment of effort: we found that participants' pattern of gaze during the high-demand choices reflected less information sampling, both in terms of between-option comparisons and within-option attribute integration. Together, these results suggest that while the high-demand options are rated as more demanding, associated with slower responses, and avoided, when possible, they are associated with overall effort disengagement.

Beyond costs-benefit trade-offs, recent work has outlined the importance of response efficacy—the relationship between the effort invested and task performance—in the decision to expend effort (Frömer et al., 2021). Under certain conditions, there can be a non-monotonic relationship between effort and task performance. For example, participants may choose to withhold effort during an impossible task where greater exertion would not improve performance. This non-monotonic relationship also suggests that the prospect of higher rewards may not yield improvements in performance. As such, previous work has noted performance decrements in response to larger reward prospects (Lee & Grafton, 2015). Indeed, some previous work has demonstrated people's sensitivity to the marginal value of effort by contrasting performance-contingent to random rewards (Frömer et al., 2021; Shenhav et al., 2013; Späti et al., 2014). On this view, effort should only be invested when increasing effort investment confers larger performance benefits—i.e., the marginal value of effort (R. Otto et al., 2021). Aligned with this view, we find that participants speed-up their responses and sample less information as indexed by their gaze when both the reward on offer and the strategic conflict are high. Put another way, participants may be withholding their effort when the marginal benefits of effort are low and the opportunity cost of time is high (Otto & Daw, 2019). This suggests that participants may be disengaging their effort to resolve deadlocks and maximize long-term rewards (Pirrone et al., 2018). Echoing this interpretation, we find that participants' information sampling was predictive of making an EV maximizing choice but only for the low-conflict choices, suggesting that effort in decision-making for the high-demand choices is unrelated to obtaining rewards. Together, our results suggest that individuals will only invest effort in value-based choices when their efforts are associated with greater task performance and rewards.

In light of these results, this suggests that people may not be pure cognitive misers as the law of least (cognitive) work would suggest (Hull, 1943; Kool et al., 2010). Recent theoretical work has focused on the situations in which people purportedly seek cognitive effort all else being equal (Inzlicht et al., 2018). While we demonstrate that people will avoid demanding value-based choices, pure cognitive effort avoidance would suggest that participants should in fact be selecting the high-demand decisions, in which they seem to invest the least amount of effort, as evidenced by their gaze and pupil diameter. Yet, participants show a marked preference for the low-demand choices across two experiments, with no associated decrease in either pupil dilations or information sampling in the test phase of the task. One possible interpretation is that in addition to minimizing effort costs, people may be optimizing other signals like subjective feelings of confidence. Indeed, recent work in value-based choice suggests that individuals may be trading-off effort costs for feelings of confidence (Lee & Daunizeau, 2021). While we found that participants did feel more confident when responding to the low-demand choices, future work is needed to corroborate whether preference for these choices reflects a metacognitive trade-off between effort and confidence. Future work should also assess whether this trade-off extends to cognitive control or is specific to value-based choice.

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Section 4.7: Supplemental Materials

Digit Symbol Coding

To measure processing speed, participants were asked to complete a computerized version of the Digit-Symbol Coding task (Mathias et al., 2017; Salthouse, 1985). During this task, participants are shown a static list of 9 digit-symbol pairs, which remain visible at the top of screen for the entirety of the task. On each trial, participants are asked to indicate whether the digit-symbol pair presented in the centre of the screen matches one of the 9 digit-symbol pairs depicted at the top of the screen. Yes/No responses were made using the left and right arrow keys, with the response-key mappings counterbalanced between participants.

Operation Span Task

To measure individual differences in working memory capacity, we asked participants to complete the automated version of the Operation Span Task (Ospan; Unsworth et al., 2005). In this task, participants are asked to encode and recall a sequence of letters while completing simple arithmetic problems between the presentation of each letter. Immediately after being presented with a letter, participants were asked to solve a simple arithmetic problem and answer whether the proposed solution on the screen was correct or incorrect. Letters were presented in sets of different sizes ranging from 3 to 7 letters. Working memory capacity was quantified by the Ospan score which was computed as the sum of all correctly recalled set sizes (Unsworth et al., 2005).

Need For Cognition Scale

To measure individual differences in motivation to engage in effortful thinking, we asked participants to complete the Need for Cognition scale (NFC; Cacioppo et al., 1984). The scale consists of 18 items which participants rated how characteristic they thought each statement was of themselves on a scale of 1-5, 1 being extremely uncharacteristic and 5 being extremely characteristic. Example items include: “Thinking is not my idea of fun” and “I would prefer complex to simple problems”.

Maximization Scale

To measure individual differences in decision strategy, we asked participants to complete the short form of the Maximization scale (Nenkov et al., 2008). The scale consists of 6 items which participants rated how characteristic they thought each statement was of themselves on a scale of 1 – 7, 1 being extremely uncharacteristic and 7 being extremely characteristic. Example items include: “I never settle for second best” and “No matter what I do, I have the highest standards for myself”. Scores on the scale are designed to differentiate between dispositional “maximizers”—those who try to choose the “best” option—and “satisficers”—those who rather settle for a “good enough” option.

Table S1.

High demand stimuli used for the demand rating and demand avoidance tasks.

Option 1				Option 2			
Outcome1	P(O1)	Outcome2	P(O2)	Outcome1	P(O1)	Outcome2	P(O2)
$220	0.13	$353	0.87	$708	0.3	$177	0.7
$597	0.4	$167	0.6	$248	0.16	$356	0.84
$252	0.12	$414	0.88	$815	0.35	$168	0.65
$214	0.34	$248	0.66	$311	0.45	$176	0.55
$241	0.4	$55	0.6	$90	0.15	$136	0.85
$136	0.11	$245	0.89	$562	0.25	$124	0.75
$334	0.45	$143	0.55	$192	0.23	$240	0.77
$219	0.14	$327	0.86	$570	0.4	$139	0.6
$169	0.4	$91	0.6	$108	0.29	$128	0.71
$155	0.15	$224	0.85	$406	0.3	$131	0.7
$504	0.25	$105	0.75	$115	0.1	$215	0.9
$141	0.4	$73	0.6	$88	0.28	$105	0.72
$68	0.13	$105	0.87	$204	0.3	$56	0.7
$490	0.4	$151	0.6	$216	0.17	$301	0.83
$128	0.12	$214	0.88	$428	0.35	$83	0.65
$331	0.35	$122	0.65	$153	0.19	$205	0.81
$315	0.45	$139	0.55	$185	0.24	$229	0.76
$296	0.4	$121	0.6	$157	0.23	$201	0.77
$185	0.26	$228	0.74	$328	0.35	$157	0.65
$170	0.13	$273	0.87	$547	0.3	$137	0.7
$134	0.35	$155	0.65	$198	0.4	$114	0.6
$590	0.45	$172	0.55	$274	0.17	$378	0.83
$142	0.14	$212	0.86	$413	0.25	$132	0.75
$105	0.08	$239	0.92	$630	0.25	$94	0.75
$126	0.14	$197	0.86	$372	0.35	$88	0.65
$169	0.45	$60	0.55	$87	0.19	$114	0.81
$349	0.3	$52	0.7	$74	0.09	$148	0.91
$370	0.3	$105	0.7	$128	0.14	$194	0.86
$236	0.4	$104	0.6	$132	0.25	$165	0.75
$322	0.35	$71	0.65	$104	0.13	$167	0.87
$92	0.11	$161	0.89	$345	0.3	$71	0.7
$131	0.18	$182	0.82	$305	0.35	$102	0.65
$194	0.2	$255	0.8	$378	0.45	$132	0.55

$414	0.3	$122	0.7	$147	0.14	$220	0.86
$433	0.3	$70	0.7	$97	0.1	$188	0.9
$494	0.4	$169	0.6	$233	0.18	$314	0.82
$212	0.27	$259	0.73	$358	0.4	$172	0.6
$812	0.35	$162	0.65	$246	0.12	$409	0.88
$470	0.25	$142	0.75	$153	0.13	$235	0.87
$402	0.4	$162	0.6	$211	0.21	$271	0.79
$637	0.35	$175	0.65	$238	0.14	$353	0.86
$160	0.4	$183	0.6	$225	0.45	$132	0.55
$150	0.16	$215	0.84	$386	0.3	$127	0.7
$551	0.4	$169	0.6	$242	0.17	$338	0.83
$241	0.14	$360	0.86	$652	0.35	$177	0.65
$475	0.35	$173	0.65	$218	0.19	$293	0.81
$101	0.22	$127	0.78	$178	0.45	$75	0.55
$226	0.4	$55	0.6	$86	0.13	$129	0.87
$773	0.4	$189	0.6	$298	0.15	$444	0.85
$140	0.11	$235	0.89	$491	0.3	$110	0.7
$118	0.13	$191	0.87	$370	0.35	$80	0.65
$177	0.15	$260	0.85	$447	0.4	$114	0.6
$543	0.25	$93	0.75	$104	0.09	$216	0.91
$96	0.18	$134	0.82	$235	0.3	$81	0.7
$333	0.3	$86	0.7	$106	0.13	$168	0.87
$173	0.19	$232	0.81	$363	0.4	$126	0.6
$107	0.09	$247	0.91	$654	0.25	$95	0.75
$208	0.2	$269	0.8	$392	0.45	$146	0.55
$168	0.12	$289	0.88	$615	0.3	$129	0.7
$320	0.4	$74	0.6	$120	0.14	$181	0.86
$390	0.45	$168	0.55	$226	0.24	$281	0.76
$611	0.35	$192	0.65	$250	0.16	$355	0.84
$555	0.4	$135	0.6	$213	0.14	$318	0.86
$290	0.17	$402	0.83	$628	0.45	$182	0.55
$260	0.19	$346	0.81	$535	0.4	$192	0.6
$498	0.35	$123	0.65	$173	0.14	$267	0.86
$509	0.25	$57	0.75	$65	0.07	$178	0.93
$617	0.25	$155	0.75	$168	0.12	$284	0.88
$204	0.1	$386	0.9	$878	0.3	$149	0.7
$130	0.1	$238	0.9	$528	0.3	$98	0.7
$178	0.17	$245	0.83	$381	0.45	$113	0.55
$707	0.25	$197	0.75	$214	0.13	$341	0.87

$84	0.13	$131	0.87	$246	0.35	$60	0.65
$257	0.4	$59	0.6	$96	0.14	$145	0.86
$259	0.45	$126	0.55	$162	0.28	$195	0.72
$144	0.35	$73	0.65	$85	0.28	$103	0.72
$131	0.14	$202	0.86	$405	0.25	$121	0.75
$120	0.11	$208	0.89	$463	0.25	$110	0.75
$149	0.11	$265	0.89	$578	0.3	$113	0.7
$303	0.35	$61	0.65	$92	0.12	$153	0.88
$243	0.12	$407	0.88	$815	0.35	$158	0.65
$853	0.25	$139	0.75	$154	0.09	$333	0.91
$192	0.15	$282	0.85	$503	0.35	$143	0.65
$125	0.26	$152	0.74	$204	0.45	$97	0.55
$899	0.25	$157	0.75	$174	0.09	$360	0.91
$186	0.35	$81	0.65	$98	0.25	$124	0.75
$355	0.4	$153	0.6	$194	0.22	$245	0.78
$148	0.45	$67	0.55	$89	0.27	$109	0.73
$152	0.23	$191	0.77	$282	0.35	$128	0.65
$70	0.23	$86	0.77	$124	0.35	$60	0.65
$215	0.15	$315	0.85	$581	0.3	$180	0.7
$238	0.15	$347	0.85	$636	0.3	$200	0.7
$114	0.27	$140	0.73	$202	0.35	$96	0.65
$769	0.25	$90	0.75	$103	0.08	$273	0.92
$170	0.1	$329	0.9	$758	0.3	$123	0.7
$146	0.12	$239	0.88	$487	0.3	$117	0.7
$103	0.12	$174	0.88	$350	0.35	$66	0.65
$135	0.32	$157	0.68	$199	0.45	$110	0.55
$424	0.35	$105	0.65	$147	0.13	$227	0.87
$117	0.25	$144	0.75	$207	0.35	$100	0.65

Option 1 represents the first choice with two outcomes (G11 & G12) and their respective outcome probabilities (p11, &p12). Option 2 represents the second option with twou outcomes (G21 & G22) and their respective outcome probabilities (p21 & p22).

Table S3.

Low demand stimuli used for the demand rating and demand avoidance tasks.

Option 1				Option 2			
G11	p11	G12	p12	G21	p21	G22	p22
$101	0.22	$127	0.78	$165	0.35	$191	0.65
$395	0.4	$196	0.6	$8	0.35	$207	0.65
$280	0.17	$385	0.83	$483	0.35	$588	0.65
$451	0.17	$72	0.83	$540	0.3	$161	0.7
$310	0.4	$131	0.6	$243	0.21	$64	0.79
$116	0.14	$175	0.86	$212	0.35	$271	0.65
$91	0.12	$154	0.88	$180	0.37	$243	0.63
$75	0.17	$101	0.83	$128	0.35	$154	0.65
$637	0.15	$68	0.85	$703	0.3	$134	0.7
$801	0.3	$165	0.7	$717	0.15	$81	0.85
$255	0.18	$42	0.82	$288	0.4	$75	0.6
$701	0.17	$100	0.83	$792	0.35	$191	0.65
$143	0.45	$57	0.55	$116	0.21	$30	0.79
$136	0.3	$162	0.7	$214	0.33	$240	0.67
$260	0.35	$90	0.65	$213	0.19	$43	0.81
$293	0.35	$352	0.65	$173	0.19	$232	0.81
$261	0.33	$282	0.67	$171	0.41	$192	0.59
$240	0.18	$326	0.82	$410	0.35	$496	0.65
$561	0.36	$713	0.64	$308	0.14	$460	0.86
$90	0.32	$106	0.68	$141	0.36	$157	0.64
$332	0.35	$379	0.65	$207	0.26	$254	0.74
$422	0.38	$598	0.62	$196	0.1	$372	0.9
$379	0.36	$473	0.64	$213	0.15	$307	0.85
$104	0.17	$141	0.83	$178	0.35	$215	0.65
$450	0.45	$179	0.55	$365	0.21	$94	0.79
$183	0.38	$261	0.62	$84	0.1	$162	0.9
$365	0.34	$423	0.66	$224	0.23	$282	0.77
$458	0.4	$132	0.6	$398	0.18	$72	0.82
$460	0.3	$194	0.7	$349	0.2	$83	0.8
$259	0.3	$81	0.7	$214	0.18	$36	0.82
$304	0.21	$82	0.79	$391	0.4	$169	0.6
$116	0.32	$129	0.68	$74	0.29	$87	0.71
$204	0.21	$260	0.79	$336	0.35	$392	0.65

$222	0.2	$55	0.8	$270	0.45	$103	0.55
$347	0.35	$106	0.65	$293	0.18	$52	0.82
$91	0.32	$100	0.68	$59	0.36	$68	0.64
$116	0.23	$145	0.77	$189	0.36	$218	0.64
$132	0.26	$159	0.74	$210	0.33	$237	0.67
$186	0.21	$50	0.79	$240	0.4	$104	0.6
$232	0.4	$139	0.6	$39	0.47	$132	0.53
$411	0.25	$76	0.75	$368	0.14	$33	0.86
$260	0.36	$309	0.64	$155	0.2	$204	0.8
$216	0.13	$340	0.87	$407	0.36	$531	0.64
$399	0.18	$75	0.82	$448	0.45	$124	0.55
$93	0.21	$27	0.79	$125	0.35	$59	0.65
$694	0.17	$110	0.83	$773	0.4	$189	0.6
$378	0.37	$519	0.63	$186	0.11	$327	0.89
$398	0.35	$149	0.65	$318	0.2	$69	0.8
$139	0.34	$147	0.66	$93	0.6	$101	0.4
$109	0.34	$121	0.66	$70	0.34	$82	0.66
$539	0.18	$91	0.82	$609	0.4	$161	0.6
$76	0.1	$140	0.9	$160	0.37	$224	0.63
$157	0.36	$208	0.64	$82	0.13	$133	0.87
$534	0.3	$106	0.7	$481	0.15	$53	0.85
$341	0.36	$411	0.64	$200	0.18	$270	0.82
$569	0.18	$94	0.82	$641	0.4	$166	0.6
$212	0.36	$252	0.64	$126	0.19	$166	0.81
$259	0.45	$126	0.55	$6	0.35	$139	0.65
$515	0.35	$128	0.65	$454	0.17	$67	0.83
$84	0.13	$131	0.87	$157	0.35	$204	0.65
$607	0.4	$153	0.6	$542	0.17	$88	0.83
$130	0.37	$175	0.63	$66	0.12	$111	0.88
$282	0.4	$147	0.6	$16	0.37	$151	0.63
$203	0.38	$292	0.62	$92	0.1	$181	0.9
$194	0.14	$289	0.86	$353	0.36	$448	0.64
$575	0.18	$100	0.82	$655	0.4	$180	0.6
$483	0.25	$83	0.75	$437	0.14	$37	0.86
$140	0.12	$244	0.88	$282	0.37	$386	0.63
$476	0.45	$132	0.55	$424	0.18	$80	0.82
$195	0.84	$207	0.16	$287	0.3	$299	0.7
$383	0.18	$71	0.82	$443	0.4	$131	0.6
$244	0.4	$88	0.6	$201	0.19	$45	0.81

$183	0.37	$266	0.63	$82	0.1	$165	0.9
$103	0.12	$174	0.88	$203	0.36	$274	0.64
$522	0.18	$90	0.82	$616	0.35	$184	0.65
$202	0.35	$245	0.65	$118	0.18	$161	0.82
$122	0.14	$185	0.86	$224	0.36	$287	0.64
$326	0.35	$390	0.65	$194	0.2	$258	0.8
$397	0.45	$186	0.55	$305	0.22	$94	0.78
$193	0.23	$244	0.77	$315	0.35	$366	0.65
$195	0.11	$360	0.89	$409	0.37	$574	0.63
$492	0.17	$72	0.83	$601	0.25	$181	0.75
$108	0.21	$31	0.79	$141	0.4	$64	0.6
$125	0.2	$167	0.8	$211	0.36	$253	0.64
$470	0.36	$578	0.64	$269	0.16	$377	0.84
$124	0.33	$146	0.67	$194	0.36	$216	0.64
$162	0.15	$235	0.85	$289	0.36	$362	0.64
$168	0.12	$284	0.88	$332	0.37	$448	0.63
$215	0.37	$294	0.63	$106	0.11	$185	0.89
$467	0.3	$67	0.7	$439	0.14	$39	0.86
$818	0.12	$56	0.88	$873	0.25	$111	0.75
$230	0.18	$313	0.82	$394	0.36	$477	0.64
$703	0.16	$94	0.84	$782	0.35	$173	0.65
$306	0.36	$373	0.64	$177	0.17	$244	0.83
$218	0.24	$274	0.76	$354	0.34	$410	0.66
$149	0.21	$39	0.79	$189	0.4	$79	0.6
$685	0.12	$46	0.88	$729	0.25	$90	0.75
$202	0.3	$53	0.7	$173	0.17	$24	0.83
$787	0.25	$143	0.75	$707	0.14	$63	0.86
$590	0.45	$172	0.55	$520	0.19	$102	0.81

Option 1 represents the first choice with two outcomes (G11 & G12) and their respective outcome probabilities (p11, &p12). Option 2 represents the second option with twou outcomes (G21 & G22) and their respective outcome probabilities (p21 & p22).

Table S3.

Comparing Easy and Hard stimuli.

	Parameter	Easy Stimuli	Hard Stimuli	T	df	p
Option1	Outcome 1	311.16	291.09	0.73	197.73	0.46
Option 1	Outcome 1	190.08	181.29	0.55	172.47	0.58
Option 1	SD	133.70	136.06	-0.13	196.72	0.89

Option 1	P(O1)	0.28	0.26	1.10	197.99	0.27
Option 2	Outcome 1	303.37	304.29	-0.03	197.96	0.97
Option 2	Outcome 2	193.49	176.93	1.05	172.62	0.30
Option 2	SD	133.70	143.50	-0.55	197.13	0.58
Option 2	P(O1)	0.28	0.26	1.39	197.98	0.17
Option 1	EV	220.58	226.21	-0.41	180.83	0.68
Option 2	EV	222.15	226.25	-0.29	174.63	0.77
Option 1	Ratio (O1/O2)	2.66	2.18	1.42	176.75	0.16
Option 2	Ratio (O1/O2)	2.65	2.23	1.27	166.94	0.21
Option 1	Coefficient of variation	0.73	0.59	1.62	157.24	0.11
Option 2	Coefficient of variation	0.76	0.61	1.67	153.45	0.10
	EV Option1 – EV Option2	-3.40	-0.04	-0.28	99.00	0.78

Parameter represents what is being compared between the stimulus sets. For example, the first row represents a t-test between the first outcome of the first option between easy and hard choice sets

Table S4.

Results of the hierarchical Poisson regression on number of gaze switches during the learning phase as a function of choice demand, trial, and Reward on Offer.

Predictors	*Log-Mean*	*CI*	*p*
(Intercept)	*0.80*	*0.73 – 0.86*	*<0.001*
Choice Difficulty (Easy vs. hard)	*-0.06*	*-0.12 – -0.01*	*0.032*
Trial (Learning phase)	*0.00*	*-0.03 – 0.04*	*0.804*
Reward on Offer (Z Score)	*0.01*	*-0.02 – 0.03*	*0.480*
*Difficulty * Reward*	*-0.05*	*-0.09 – -0.02*	*0.004*

Table S5.

Results of the hierarchical Linear regression on total Euclidean distance covered in the first second during the learning phase as a function of choice demand, trial, and Reward on Offer.

Predictors	*Estimates*	*CI*	*p*
(Intercept)	*1524.77*	*1449.98 – 1599.55*	*<0.001*
Choice Difficulty (Easy vs. hard)	*-40.85*	*-67.31 – -14.39*	*0.002*
Trial (Learning phase)	*1.79*	*-10.92 – 14.51*	*0.782*
Reward on Offer (Z Score)	*-4.69*	*-21.10 – 11.72*	*0.576*
*Difficulty * Reward*	*-19.61*	*-37.52 – -1.69*	*0.032*

Table S6

Results of the hierarchical Logistic regression EV maximizing choice during the learning phase as a function of choice demand, trial, and total Euclidean distance covered in the first second.

Predictors	*Log-Odds*	*CI*	*p*
(Intercept)	*2.49*	*2.23 – 2.75*	*<0.001*
Trial (Learning phase)	*0.14*	*0.03 – 0.26*	*0.017*
Choice Difficulty (Easy vs. hard)	*-2.60*	*-2.86 – -2.33*	*<0.001*
Euclidean Distance	*0.44*	*0.27 – 0.60*	*<0.001*
*Difficulty * Distance*	*-0.41*	*-0.60 – -0.22*	*<0.001*

Section 5: Bridging Text

In the previous section, we examined three open research questions my thesis aims to address. First, we sought to better understand whether value-based decision-making demands could be manipulated without assuming *a priori* the strategy decision-makers use to choose. We hypothesized that choices high strategic conflict arising from conflicting responses from different decision-making strategies and low discriminability in terms of EV would be rated as more demanding. Indeed, this was reflected in participants' subjective ratings of demand. Secondly, we sought to test the main prediction of Cost-Benefit models (Frömer et al., 2021; Kool et al., 2010; Kurzban et al., 2013; Shenhav et al., 2017; Silvetti et al., 2018) of effort allocation: demand should be avoided all else being equal. Again, we found participants avoided demanding value-based choice, providing support for this hypothesis. Finally, we tested whether pupil diameter—a marker of momentary effort allocation—during value-based decisions tracks both within individual changes in demand and between individual differences in demand avoidance. Below, we discuss how these findings corroborate the main aim of this thesis: unifying models of effort exertion in both cognitive control and decision-making.

As discussed above, our joint analysis of response times, gaze and pupil diameter indicates that participants were withdrawing their effort for the high-demand choices. Yet, together with the behavioural results of the earlier experiments in that section, it is difficult to determine where the choices labelled as low-demand lie on the inverted-U relationship between demand and effort. It is possible that the low-demand choices actually reflect demanding but achievable challenges implying that there are choices lower in demand than those used in the experiment. It is equally possible that the choices labelled as low demand are in fact low in demand meaning there are choices whose demand level lies somewhere between the high- and low-demand choices (i.e., medium-demand). While in the experiments discussed here, demand was manipulated in a binary fashion—conflict versus no conflict—future research should investigate whether feelings of demand can be manipulated either by varying the number of conflicting responses or other factors like the magnitude of the difference in EV.

Together with the research in Section 2, the research discussed here suggests that investigating effort exertion in both cognitive control tasks and value-based decision-making tasks can be unified. In Section 2, we show that both individuals' effort costs and available rewards modulate effort investment as indexed by pupil diameter. In Section 4, we show that when all else is equal, demanding value-based choices are avoided and effort is conserved for value-based choices where exertion does not yield performance improvements (Otto et al., 2022). We equally show that when opportunity costs are high (i.e., the decision demands and reward on offer are high), effort is withheld (Kurzban et al., 2013; Otto & Daw, 2019). These experiments suggest that pupil diameter can be used as a reliable measure of effort exertion in both cognitive control and value-based decision-making tasks. Furthermore, these experiments equally suggest that cost-benefit models can capture effort exertion in both cognitive control and value-based decision-making tasks.

Section 6: Discussion

Across four experiments, my research has investigated why we sometimes deliberate effortfully, and other times rely on habitual or effortless strategies. The results of my thesis bridge theories on effort exertion in cognitive control and value-based decision-making— two fields in psychology which have largely progressed independently—and suggest that cost-benefit models of effort allocation are a viable framework for understanding effort across domains. Furthermore, my thesis leverages varied techniques to understand not only metacognitive (i.e., subjective feelings of demand) and behavioural (i.e., avoidance) consequences of previous effort investment but also physiological markers of momentary effort allocation. In the first manuscript, I leveraged cost-benefit models of effort exertion to demonstrate the momentary changes in pupil diameter track individual differences in effort costs—indexed by Stroop costs—and reward-induced effort exertion. In the second manuscript, we show that strategic conflict in value-based choices is experienced as demanding, and avoided when all else is equal. I anticipate that my thesis will help refine our models of cognitive effort investment and provide the groundwork (e.g., stimuli, tasks, and measures) for future research on effort in value-based choices.

The experiments in this dissertation have provided novel insights into the allocation of cognitive effort in both cognitive control and value-based decision-making tasks. First, we helped corroborate pupil diameter as a reliable index of momentary changes in within-person effort exertion. Prior to this study, it remained unclear whether pupil diameter could be used as an indicator of within-person changes in pupil dilation as the wealth of evidence was from between-subjects designs (van der Wel & van Steenbergen, 2018). In section 2, we leveraged Cost-Benefit models of effort allocation (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017) to show reward-induced changes in pupil diameter predicted reward-induced changes in task performance. Second, we demonstrated demand avoidance in value-based choices independent of choice preference with a novel experimental paradigm. While previous work had established demand avoidance for cognitive control tasks control (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010; McGuire & Botvinick, 2010; Vogel et al., 2020; Westbrook & Braver, 2015) and a preference for less complex options (Zilker et al., 2020) or the status quo (Inman & Zeelenberg, 2002; Ritov & Baron, 1992; Samuelson & Zeckhauser, 1988; Tsiros & Mittal, 2000), it remained unclear whether this reflected demand avoidance or a preference for other choice features. This was particularly unclear as the use of heuristics is often assumed to be less effortful (Evans, 2003; Evans & Stanovich, 2013; Gigerenzer & Todd, 1999), however, there are some notable exceptions (Bobadilla-Suarez & Love, 2018; Thomson & Oppenheimer, 2021). In Section 4, we developed a novel paradigm to address these concerns by first validating choice sets using subjective demand ratings and leveraging a demand selection paradigm (Kool et al., 2010). Finally, we demonstrate that demand avoidance in value-based choice is predicted by individual differences in momentary effort exertion. While previous work has demonstrated demand avoidance for cognitive control tasks predicts individual differences in cognitive task performance (Kool et al., 2010) there is considerably less work linking momentary effort exertion and demand avoidance. This is particularly important as it remains unclear whether those who demonstrate near chance-level (i.e., 0.5) preferences are indifferent or have failed to learn the task structure. In section 4, we leverage our novel experimental paradigm to demonstrate that effort exertion—indexed here by pupil diameter —during low-demand value-based choices predicts later demand avoidance. Together, the experiments outlined here demonstrate how effort exertion in value-based choice can be measured and studied using physiological, behavioural, and metacognitive methods.

While previous theories on value-based choice like Dual process theory posit that we use heuristics to avoid effort investment (Evans, 2003; Evans & Stanovich, 2013; Frederick, 2005), there is considerably less work which measures and predicts when effort is invested as people are assumed to exert themselves when they are not using heuristics to decide (Thomson & Oppenheimer, 2021). Yet, recent work shows that heuristics may be more effortful as they require attentional control to implement when compared to more deliberative strategies like computing differences in EV (Bobadilla-Suarez & Love, 2018). To address this, we investigated this assumption by measuring pupil dilations while deciding in section 4 and show demanding value-based choices may not always elicit greater effort investment. This finding raises the question of whether momentary effort investment or trait-level demand avoidance predicts heuristic use, as posited by Dual Process models (Diederich & Trueblood, 2018; Evans, 2003; Evans & Stanovich, 2013). Further research is needed to test whether trait-level demand avoidance predicts individuals' tendency to rely on heuristics across decision problems more generally, or whether it depends on the kinds of decisions or heuristics used. Furthermore, it remains unclear whether the strength of the relationship between heuristic use and demand avoidance in value-based choice depends on the amount of effort (e.g., how much working memory capacity, attentional control etc.) each heuristic requires to be implemented. Interestingly, theories of heuristic use like Dual Process theory also assume that effort in value-based choice tends to lead decision-makers to EV maximizing choice (Diederich & Trueblood, 2018). Yet, in experiments 2 and 3 of Section 4, we show that longer deliberation was not associated with more EV maximizing choice. Considering the results of this thesis, perhaps this view is not complete and requires the consideration of the marginal value of effort in value-based choice.

Other models of cognitive effort allocation like the Motivational Intensity Theory (Brehm & Self, 1989) highlight the importance of the marginal value of effort—"Is *increasing my cognitive effort investment worth it?*". While effort exertion usually confers gains on task performance, there are certain situations in which increasing effort exertion may not yield proportionally larger improvements in task performance. Researchers have recently demonstrated that decision-makers are sensitive to this marginal value of effort and modulate their exertion in proportion to the efficacy of their responses (Frömer et al., 2021; Otto et al., 2022). When efficacy is high and task performance is strongly dependent on effort exertion, people tend to invest more effort when compared to situations where efficacy is low, and their task performance is decoupled from their effort. Aligned with these findings, we saw in the second section that people invest more effort when they are rewarded for correct responses in a cognitive control task. In section 4, however, we saw that when rewards were highest, people withdrew their effort—indexed both by faster response times and less information sampling—for demanding decisions. While these results seem contradictory, they are both aligned with the predictions of cost-benefit models which include the marginal value of effort (Frömer et al., 2021; Otto et al., 2022). In section 2, greater effort investment was associated with better task performance—smaller switch costs—and more rewards. Yet, in section 4 greater effort investment for demanding choices did not yield more EV maximizing choices (i.e., rewards). Thus, while theories of value-based decision-making posit that effortful deliberation (i.e., not using heuristics) leads to more EV maximizing (i.e., unbiased) choices (Diederich & Trueblood, 2018; Evans & Stanovich, 2013; Gigerenzer & Todd, 1999), the results outlined in my thesis suggest that effort is only allocated when it confers larger rewards, which is not the case for demanding value-based choices. Together with other work which suggests that heuristic use may place a greater tax on attentional control (Bobadilla-Suarez & Love, 2018), these results suggest that the marginal value of effort may differ between different decision strategies and guide which strategy is ultimately used. Future work is needed to directly test whether people are equally sensitive to the marginal value of effort in value-based choice.

Despite the experiments in Section 4, it remains unclear which specific factors make a value-based choice demanding. In the first experiment of section 4, we show that decisions where there is low discrimination between the options in terms of expected value and decisions in which there is conflict between the heuristic responses are rated as more demanding. Thus, it remains unclear if choices are deemed as more demanding due to the increase in strategic conflict, their low discriminability or both. While this was not a research question explored in this thesis, it remains a limitation of the experiments in section 4. Previous work has increased task demands in value-based choice by placing environmental constraints on available time (Guo et al., 2017; Hu et al., 2015; Madan et al., 2015; Olschewski & Rieskamp, 2021; Zur & Breznitz, 1981) or taxing cognitive load (Hinson et al., 2003, 2019; Whitney et al., 2008). While it is reasonable to assume that these kinds of manipulations may tax the cognitive resources (i.e., information processing and working memory capacity) needed to decide, they also assume that more effortful strategies are used when there are no constraints—an assumption that has yet to be confirmed. As mentioned above, the discriminability (i.e., similarity) of two options has also been used to manipulate the decision demand (Lebreton et al., 2009; Lee & Daunizeau, 2021). However, this assumes that decision-makers are attending to and using the expected values to decide, which may not always be the case when using heuristics like Maximax and Maximin (Coombs et al., 1970). Others have used similar approaches to define decision demand as the amount of information to be processed like the number of options (Iyengar & Lepper, 2000) or the complexity of the options (Bernheim & Sprenger, 2020; Huck & Weizsäcker, 1999; Sonsino et al., 2002; Zilker et al., 2020). However, these approaches to defining decision demand are agnostic to the amount of cognitive control needed to execute a given heuristic (Frömer & Shenhav, 2021; Thomson & Oppenheimer, 2021). Other more fundamental approaches have relied on the number of Elementary Information Processes (EIP) (Johnson & Payne, 1985; Payne et al., 1993) needed to decide. Yet this approach is limited as it relies on parsing information into discrete units which is arbitrary and depends on the level of granularity (Thomson & Oppenheimer, 2021). To overcome some of these challenges, we focused on the possible underlying cognitive processes when deciding and we used the conflict between different decision strategies as a proxy for the cognitive control demands (Venkatraman et al., 2009). While this approach proved successful in eliciting higher demand ratings, it failed to elicit greater pupil diameter. It is difficult to predict the demand of a choice *a priori*; more work is needed to better understand what makes a value-based choice demanding by focusing on the underlying cognitive processes (i.e., working memory, information processing, and cognitive control) recruited to decide.

Cognitive effort is defined as the intensification of mental activity using cognitive resources in service of a goal (Inzlicht et al., 2018). While this definition fits nicely in the cognitive control literature as the task demands are usually defined based on the tax it places on cognitive resources (Kurzban et al., 2013), this remains an open question for value-based decision-making. As previously discussed, research should focus on the demands placed on cognitive processes used while decision-making. For example, increasing demands on working memory could be achieved by increasing the number of options available (Iyengar & Lepper, 2000), the number of relevant attributes (Bernheim & Sprenger, 2020; Huck & Weizsäcker, 1999; Sonsino et al., 2002) or asking participants to simultaneously complete a separate task (Hinson et al., 2019; Whitney et al., 2008). Additionally, information processing could be taxed by increasing the amount of relevant information or decreasing the amount of time available to decide (Bobadilla-Suarez & Love, 2018; Guo et al., 2017; Hu et al., 2015; Madan et al., 2015; Zur & Breznitz, 1981, 1981). Information processing and attentional control are particularly relevant for implementing complex heuristics which require additional cognitive control to select the relevant information to successfully execute (Bobadilla-Suarez & Love, 2018). Cognitive control can equally help decision-makers select the optimal decision strategy or relevant information given a goal (Frömer & Shenhav, 2021; Smith & Krajbich, 2019; Thomas et al., 2019). Yet, it may be difficult to isolate a single cognitive process as many of the manipulations mentioned above tax multiple cognitive processes simultaneously. As discussed above, we show that decisions with low discriminability and strategic conflict are rated as more demanding. In addition, other cognitive processes like episodic memory have been shown to contribute to decision-making. For example, having participants engage in episodic future thinking, where they imagine themselves completing a task in a counterfactual future time and place has been shown to increase preferences for larger future rewards over small rewards now (Peters & Büchel, 2010). Similarly, participants' risk preferences were shown to change after being given an episodic induction task (St-Amand et al., 2018). Both these findings are aligned with neuroimaging data which suggests that the hippocampus plays a critical role in breaking deadlocks in value-based decision-making (Bakkour et al., 2019) and the broader theory that posits that episodic memory supports decision-making via the hippocampus (Biderman et al., 2020). Thus, future work should also explore the contributions of episodic memory and future thinking to subjective feelings of mental effort. While we are limited in concluding that increasing strategic conflict makes value-based choices more demanding, it highlights the importance of manipulating the demands on the presumed cognitive processes underlying value-based decision-making. It also highlights the need to further study whether cognitive control is involved in resolving strategic conflict.

Another key limitation of the research outlined here in this thesis is it focused on risky value-based decision-making and not other forms of value-based decision-making. Here, we focused on risky value-based decision-making because it offered more experimental control over the stimuli where we could equate the rewards, risk level, and the amount of information between the choice sets. While these results suggest that demanding value-based choices are avoided when rewards are equated, it would be interesting to generalize these results to other types of decision-making like multiattribute decisions where the relevant features for deciding may be context-dependent (Busemeyer & Townsend, 1993; Frömer & Shenhav, 2021; Roe et al., 2001). This would be particularly important as there are numerous heuristics that could be applied to multiattribute decisions where each option can vary on the number of attributes and their relative importance, allowing experimenters to parametrically manipulate the degree of responses in conflict. It is possible then to test whether demands scale as a function of strategic conflict and avoidance scale with demand levels. These kinds of decisions may be more aligned with the choices faced in their daily lives. Yet, in most situations, participants have incomplete or no information about the consequences of the available options, this is studied in the domain of decision-making from experience (Hertwig & Erev, 2009), where choices are made based on previous experiences with each option. These choices have been classically understood using reinforcement-learning models (Dayan & Daw, 2008; Palminteri et al., 2015; Palminteri & Lebreton, 2021; Sutton & Barto, 2018) where preferences are formed as a function of each option's reward history. Importantly, preferences when making these kinds of decisions have been demonstrated to differ dramatically from choices made from description—where the reward contingencies and probabilities are made explicit (Hertwig & Erev, 2009). It remains unclear what would make these choices demanding and whether demanding choices would be avoided. Perhaps, similar to description-based decisions, perhaps low discriminability of reward contingencies in experienced-based choices can be used to manipulate decision demands. Thus, future work is needed to better understand demand in other kinds of value-based decisions and whether demand in these various forms of decisions would equally be avoided.

We are also limited in our ability to interpret the unexpected decrease in pupil size observed in experiment 3 in Section 4 as a withdrawal of effort. Our pupillary results suggest that participants withdrew their effort when completing the high-demand risky choices. While the both the behavioural (i.e., RT and EV maximizing choice) and eye movement data are aligned with this interpretation, we cannot rule out other possibilities. For example, the correlation between low-demand choice in the test phase and pupil dilations to low-demand choice in the learning phase may reflect individuals' general preferences (Hess & Polt, 1960). Alternatively, the observed relationship may be better explained by individual differences in learning the stimulus-choice set contingency. For example, those who learned this contingency best, may also be those with a more extreme preference for low-demand choice and larger pupillary responses. Further research is needed to help disambiguate these possibilities. Perhaps researchers could manipulate the marginal value of effort by leveraging stimuli with differing levels of task demands to test whether pupil diameter tracks effort investment.

A wealth of indirect evidence for decision avoidance exists in the literature (Anderson, 2003) and here we show direct evidence that demanding value-based decisions are avoided, yet there also exists a parallel line of work which suggests that the freedom of choice is valued irrespective of its consequences (Leotti & Delgado, 2011). There is a wealth of behavioural evidence suggesting that humans desire the freedom to choose consequences even if they are inconsequential on reward outcomes (Bobadilla-Suarez et al., 2017; Bown et al., 2003; Leotti & Delgado, 2011, 2014) or come at a financial cost (Bobadilla-Suarez et al., 2017). Neurobiologically, this preference for choice has been linked to activity in the ventral striatum (Leotti & Delgado, 2011, 2014), a brain region typically associated with reward processing (Knutson & Cooper, 2005; J. O'Doherty et al., 2004; J. P. O'Doherty et al., 2003). Together, researchers have interpreted these findings as suggesting that there is an inherent value to choosing (Bartling et al., 2014; Bobadilla-Suarez et al., 2017; Leotti & Delgado, 2011; Sunstein, 2015). At the same time, other research suggests that demanding choices are avoided when there are too many options (Iyengar & Lepper, 2000) or one of the options is more complex. Together, these results suggest a purported paradox: choices are both valued and avoided. Why would people value and even seek out the freedom to choose when choosing is experienced as demanding and engages cognitive resources? Perhaps the key to understanding these contradictory findings is captured by the response efficacy—i.e., the association between actions and their rewards—in cost-benefit models of effort allocation (Frömer et al., 2021; Kurzban et al., 2013; Shenhav et al., 2017). Cost-benefit models predict that demanding choice should be avoided when all else is equal (Hull, 1943; Kool et al., 2010; Kurzban et al., 2013). Indeed, across two experiments we found that demanding value-based choices were avoided. Yet, most experiments reporting a value of choice contrast a condition where choices have high response efficacy to a condition without response efficacy (Bobadilla-Suarez et al., 2017; Leotti & Delgado, 2011, 2014). Thus, it is possible that response efficacy is valued above and beyond the costs associated with effortful deliberation. More research is needed to better understand why choice is both valued and avoided.

Outside the lab, there is evidence that value-based choices can be taxing and are affected by extraneous factors. For example, there is some evidence that judicial decisions are swayed by the time since the last break (Danziger et al., 2011). Other work shows that demanding choices are even avoided, like a recent online webpage by Levitt (2021) which offered decision-makers struggling with decision paralysis the opportunity to flip a coin instead. This researcher surveyed these decision-makers after 2 and 6 months and found that they were more likely than chance to follow the advice of the coin (Levitt, 2021). Interestingly, these participants were also more satisfied with their decision and happier after 6 months when the coin suggested making a change over maintaining the status quo. This raises the question: what is the impact of decision avoidance on satisfaction, regret, and overall well-being? Does avoiding hard decisions make impact one's happiness? On the one hand, avoiding demanding decisions requires forgoing more deliberative decision strategies which can result in higher rewards. On the other hand, avoiding demanding decisions can free cognitive resources and time to invest in more rewarding activities. This distinction between laboriously trying to maximize rewards and selecting "good-enough" strategies is captured by the cognitive styles of maximizing and satisficing respectively (Schwartz et al., 2002). Importantly, these individual differences in cognitive styles are thought to predict a number of important psychological outcomes. For example, maximizers have been found to be associated with lower levels of self-esteem, happiness, and well-being (Schwartz et al., 2002). Maximizers have been equally found to suffer from more regret in their choices and endorse more symptoms of depression (Iyengar et al., 2006; Schwartz et al., 2002). Although there are some mixed findings which suggest that maximizing may not consistently predict lower life satisfaction (Dalal et al., 2015; Diab et al., 2008). Perhaps this is because there is a difference between those who actually engage in maximizing strategies and those who simply strive to be maximizers, where the goal of maximizing is uniquely associated with poorer well-being (Vargová et al., 2020). This distinction between behaviour and self-report was mirrored here, as we found that individuals consistently avoid demanding value-based choices, yet this trait was not found to relate to trait-level tendencies of satisficing. Furthermore, the results outlined in this thesis highlight the importance of the marginal value of effort (Otto et al., 2022) whereby effort is only exerted when it confers benefits to both task performance and performance-contingent rewards. Perhaps, this dependency between effort, performance and rewards is an important factor in determining the affective consequences of engaging in either cognitive style. For example, maximizing might be better suited to situations where the marginal value of effort is high rather than in situations where there is a decoupling of either the relationship between effort and performance or performance and reward. Future work is needed to better understand the downstream affective consequences—well-being, happiness, regret etc.—of demand avoidance on decision-makers.

Section 7: Final Conclusions

While the judgement and decision-making literature and the cognitive control literature have—for the most part—developed independently, they both are based on the understanding of cognitive effort—how individuals choose to allocate their cognitive resources (Thomson & Oppenheimer, 2021). Across four experiments, we sought to test whether demand in risky value-based choices is avoided like in the cognitive control domain by leveraging pupillometry and eye-tracking. Our results indicate that pupil diameter is a viable measure of momentary effort investment in cognitive control tasks, tracking both individual differences in cognitive capacity and reward-induced effort investment. We equally show that pupil diameter can be used in value-based choice to index effort exertion, controlling for differences in total reward, risk, and the number of outcomes. Behaviourally, we demonstrated that people find choices with smaller differences in expected value and more strategic conflict as more demanding and will avoid these demanding value-based choices when given the choice, all else being equal. Together, these findings suggest that risky value-based choices are experienced as demanding and avoided unless rewards offset the costs of effort investment—suggesting that cost-benefit models of effort investment provide a possible unifying framework between effort in both value-based and cognitive control tasks.

Understanding effort in risky value-based decisions is complex the demand level depends on the decision process used to choose. Often, researchers assume that employing heuristics is less effortful because they are faster or require less information to implement (Diederich & Trueblood, 2018; Evans & Stanovich, 2013; Frederick, 2005; Gigerenzer & Todd, 1999; Goldstein & Gigerenzer, 2002; Guo et al., 2017). Yet, some research suggests that successful heuristic implementation may require attentional control or other cognitive abilities (Bobadilla-

Suarez & Love, 2018), making it unclear whether heuristic use truly reflects less effort investment. The research outlined in this thesis provides evidence for new behavioural and physiological ways of assessing effort investment in risky value-based decision-making. Here we similarly discuss how the cost-benefit framework of effort investment can serve as a unifying framework for the study of effort investment in both the domains of value-based choice and cognitive control. The work described in this thesis marks the initial steps to measuring, predicting, and understanding effort allocation in value-based work. However, future work is needed to corroborate which cognitive mechanisms are engaged when deciding between risky value-based options, how they contribute to feelings of demand, and how they differentially contribute to the cost-benefit decision to allocate effort.

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