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SPECIAL ISSUE/NEUROSCIENCE OF EFFORT

Demand avoidance in value-based choice under risk: A behavioral and pupillometric examination

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Abstract

Why does decision-making sometimes feel demanding while other times feel effortless? The dominant view of cognitive effort suggests that, all else being equal, individuals prefer to avoid mentally effortful courses of action—an empirical phenomenon that has been well-studied in cognitive control paradigms. However, less work has investigated cognitive demand avoidance in value-based decisions. Here we investigate subjective (self-reported) demand, preferences for demand, and psychophysiological measures of effort outlay in the context of risky decision-making. Across three experiments ($N = 199$), we observe that individuals evaluate choice pairs—consisting of two options with described risk levels and reward magnitudes—with less discriminable expected value differences as subjectively more demanding. More interestingly, participants exhibit a robust preference for low-demand risky choice pairs in a novel Decision Demand Task, which we modeled after a well-characterized demand selection paradigm used in the cognitive control domain. Finally, using pupillometry, we find that participants, contrary to our expectations, exhibit larger task-evoked pupillary responses (TEPRs)—a well-characterized measure of momentary effort exertion—when choosing between low-demand versus high-demand risky choice pairs, and that these TEPR magnitudes predicted subsequent demand-avoidant preferences. Together, these results demonstrate that cognitive demand avoidance generalizes beyond cognitive control tasks to risky value-based choice.

Keywords Decision-making · Effort · Pupillometry · Demand · Risk

Introduction

A central tenet of theories of decision-making is that individuals are reluctant to engage in cognitively costly forms of information processing (Gigerenzer & Gaissmaier, 2011; Payne et al., 1993). On this view, when people are faced with complex choices, they often employ simplifying heuristics in order to avoid effortful cognitive processing (Oprea, 2024; Shah & Oppenheimer, 2008) or will delay or even avoid making choices entirely (Anderson, 2003; Dhar, 1996). At the same time, a growing body of work investigating the phenomenology of mental effort observes, nearly ubiquitously, that individuals, when faced with the choice, avoid cognitively demanding courses of action (Kool & Botvinick, 2018; Vogel et al., 2020). In turn, this observed preference against effortful mental activity has spurred a more recent line of empirical work observing that individuals evaluate cognitively effortful situations as costly and unpleasant (David et al., 2024; Devine et al., 2023; Otto et al., in press).

While previous investigations of cognitive effort avoidance have typically operationalized cognitive effort in terms of cognitive control demand—for example, in well-studied response conflict (Desender et al., 2017) and task-switching paradigms (Devine & Otto, 2022; Kool et al., 2010)—or in terms of working memory and/or attentional demands (Bogdanov et al., 2022b; Chong et al., 2017; Vogel et al., 2020; Westbrook et al., 2013), it is unclear whether individuals avoid effortful value-based choices in the same way. In other words, do people also avoid circumstances where they face difficult choices—for example, between two similarly valued options in favor of choices between two options with more distinct values?

However, one challenge inherent in understanding demand avoidance in the domain of value-based choice is operationalization of choice demand itself. On the basis of an enormous body of work suggesting that deciding between prospects with uncertain outcomes—e.g., a 10% chance to

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win $100 and $0 otherwise versus $10 with certainty—requires effortful, deliberate processing of probability and outcome information (Brandstätter et al., 2006; Johnson & Payne, 1985; Oprea, 2024; Slovic et al., 2005), we reasoned that risky decision-making naturally affords parametric manipulation of information processing demand. More specifically, we reasoned that the difficulty in discriminating between the expected values of uncertain prospects would influence the subjective demand evoked by choice. For example, previous work has used differences in expected value (EV)—the sum of possible outcome values multiplied by the probability of each possible outcome occurring—to manipulate decision conflict (Venkatraman et al., 2009a). Buttressing the idea that low value discriminability engenders choice difficulty, recent studies have observed that that smaller differences in EV between risky options leads to slower choices, accompanied by lower self-reported confidence (da Silva Castanheira et al., 2021a; Hoven et al., 2023). Likewise, when choosing between concrete goods where outcomes are certain, choices between options with similar subjective values are typically made more slowly (De Martino et al., 2013; Lebreton et al., 2009) and are accompanied by greater self-reported decision effort (Lee & Daunizeau, 2021), relative to choices between options with large differences in subjective value.

Accordingly, to better understand how cognitive effort avoidance manifests in value-based choice, we examined the possibly that individuals experience risky choices as subjectively demanding and, when given the choice, prefer to avoid making effortful risky choices in favor of less effortful risky choices. To do this, we pose the following three specific questions. First, can we effectively manipulate the subjective (i.e., self-reported) effort associated with risky choices by changing the properties of the risky choice pairs themselves? Second, when faced with a choice, do people systemically avoid risky choices that are experienced as effortful? Third, do physiological indices of momentary effort exertion—namely, task-evoked pupil diameter changes (da Silva Castanheira et al., 2021b; van der Wel & Steenbergen, 2018)—evoked by risky decision-making relate to individuals' preferences to avoid effortful risky choices?

To this end, demonstrating that we avoid cognitively demanding value-based choices under risk, much as we avoid situations with heightened cognitive control demands (Kool & Botvinick, 2018), is important for understanding the domain-generality of cognitive effort avoidance. At the same time, a direct examination of the interplay between effort avoidance and risky decision making—using self-reported effort, evoked preferences, and physiological measures of effort—would corroborate the influential notion that cognitive effort avoidance underlies many putatively irrational choice patterns in economic (i.e.,, value-based) choices (Camerer & Hogarth, 1999; Gigerenzer & Gaissmaier, 2011; Shah & Oppenheimer, 2008; Smith & Walker, 1993). Finally, a burgeoning literature in cognitive neuroscience has sought to understand how the brain—for example, in areas such as the dorsal anterior cingulate cortex (dACC)— represents effort costs, and integrates these costs with benefits (i.e., reward incentives) to efficiently direct costly cognitive processing (Edgar et al., in press; Lopez-Gamundi et al., 2021; Shenhav et al., 2013). Elucidating how psychophysiological and self-report measures of cognitive effort relate to demand avoidance in risky choice will enrich our understanding of cost–benefit effort computations presumably occurring in these brain regions.

While, to our knowledge, the question of whether individuals also avoid demanding risky value-based choices has not been addressed directly, there is ample evidence supporting the idea that in many cases, evaluating—and choosing between—risky prospects imposes considerable cognitive processing demands on decision-makers. For example, constraining individuals' ability to deliberate between options by imposing concurrent cognitive demand (Hinson et al., 2003, 2019; Whitney et al., 2008) or time pressure (Guo et al., 2017; Madan et al., 2015; Olschewski & Rieskamp, 2021) potentiates framing effects in risky choices—which are thought to arise from employing lower-effort strategies that are less deliberative in nature (Kahneman & Frederick, 2007; Loewenstein et al., 2015). Accordingly, in light of the considerable body of evidence indicating people systemically avoid situations with increased demands on executive functions (Kool & Botvinick, 2018), we reasoned that people may also avoid particularly demanding risky decisions as they may make similar demands on these same executive processes (Hinson et al., 2019; Whitney et al., 2008).

In a separate line of inquiry, cognitive effort research has typically operationalized task demand in terms of cognitive control demand, perhaps most famously using the Demand Selection Task (Kool et al., 2010). In these tasks, participants typically make repeated choices between two stimuli associated with different levels of cognitive demand—e.g., greater (versus smaller) likelihood of switching between two simple tasks. Under the assumption that more frequent switches between tasks impose increased demands for cognitive control, these studies typically find that individuals avoid choosing the (demanding) option associated with a high task switch rate in favor of the (less demanding) options associated with less frequent task switches (Bogdanov et al., 2021; Kool et al., 2010; Patzelt et al., 2019; Sayalı & Badre, 2021). Supporting the idea that demand-avoidant preferences are driven by evaluations of subjective effort, individuals rate stimuli associated with a high demand level—i.e., higher task switching rate— as subjectively more demanding (Devine & Otto, 2022; Wu et al., 2022). Here we develop a risky decision-making paradigm which sought to emulate

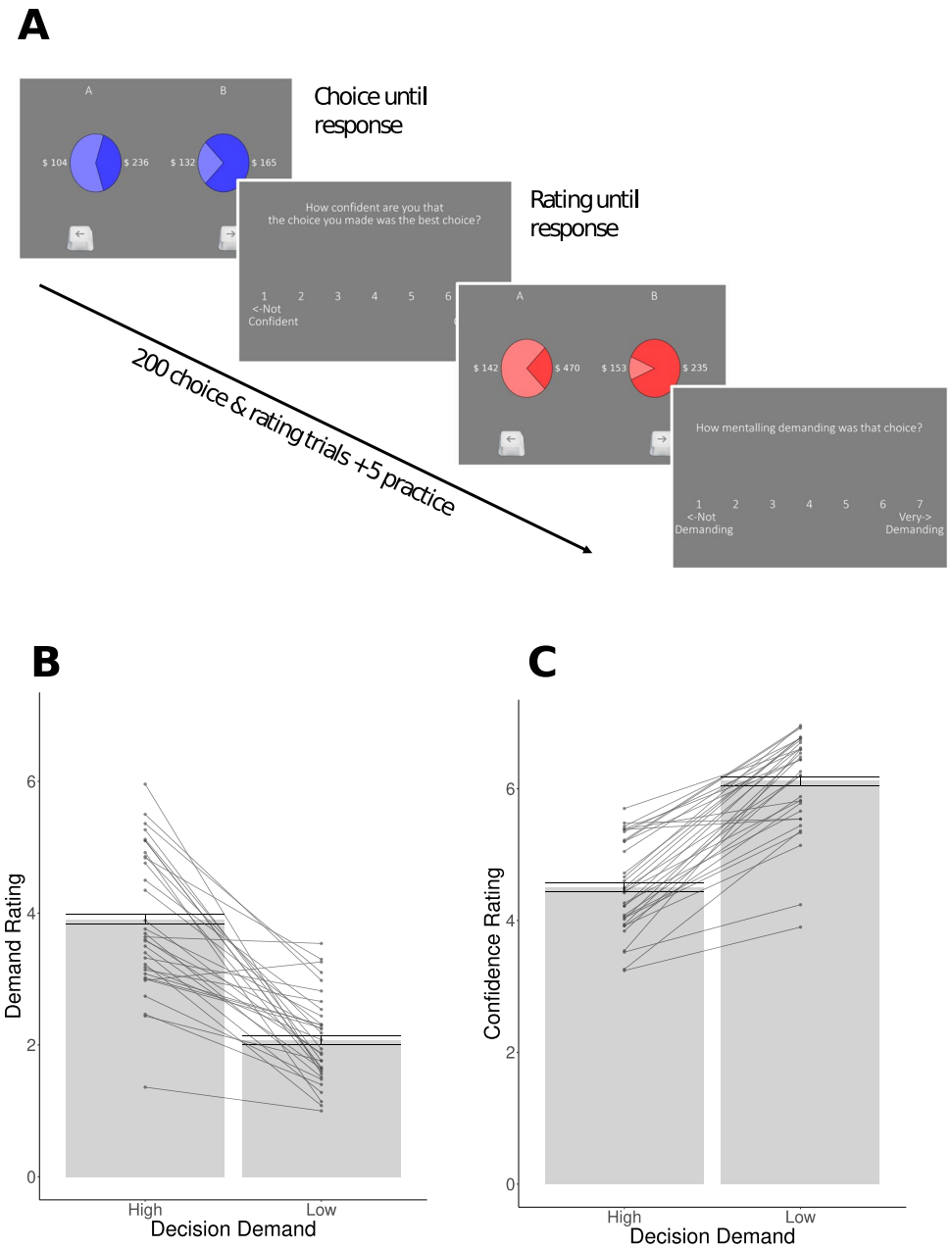

Fig. 1 (**A**) The risky decision-making task in Experiment 1. Participants were asked to choose between two risky options for whose outcomes and associated probabilities were depicted as pie charts. Choices were recorded using the right and left arrow keys. After each choice, participants were presented 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 (self-reported) cognitive demand as a function of choice pair type. (**C**) Subjective (self-reported) decision confidence as a function of demand level. Error bars represent standard error of the mean

the key properties of the Demand Selection Task in order to understand demand avoidance in the domain of risky choice.

Accordingly, in the present experiments, we operationalized cognitive demand in the risky choice setting as the discriminability of the EVs of two risky options faced by decision-makers, with the presumption that choosing between pairs of risky prospects with similar EVs (e.g., Option A: a 84% chance of winning \$355 and \$250 otherwise, EV = 338.2; versus Option B: 35% chance of \$611 and \$192 otherwise, EV = 338.65) should evoke greater subjective demand than choosing pairs of risky prospects with highly discriminable EVs (e.g., Option C: 45% chance of \$450 and \$179 otherwise, EV = 300.95; versus Option D: 55% chance of \$365 and \$94 otherwise, EV = 243.05).

To do this, we carefully constructed high-demand and low-demand choice pairs that were defined, critically, by their level of EV discriminability, but importantly, equated the other important properties of these choice pairs: for example, the average EVs and risk levels of the options. In this way, participants would not form evaluations about (or preferences between) high- and low-demand choice pairs on the basis of, for example, the overall (average) values or risk levels of the two options but instead on the basis of the difficulty in discriminating between the options' values. To discourage participants from engaging in exact EV computations based on numerical probabilities, we presented each option visually using pie charts (Fig. 1A), following previous work (De Martino et al., 2006). Finally, we also considered the possibility that individuals, rather than computing and choosing on the basis of EVs, may instead evaluate risky options using simple heuristics which do not integrate probability and outcome information (Pachur et al., 2017) and, accordingly, constructed these risky choice pairs so that low-demand (versus high-demand) choice pairs also engendered low (and high) levels of conflict between the prescriptions of two commonly used heuristics.

With this operationalization of demand in value-based choice, the present studies seek to provide an initial examination of demand avoidance in the domain of risky decision-making. First, in Experiment 1, we establish whether choosing between (high-demand) choice pairs with low EV discriminability evoke greater (self-reported) subjective cognitive demand relative to (low-demand) choice pairs with greater EV discriminability. Having established that these two types of choice pairs engender differential levels of subjective cognitive demand, in Experiment 2, we developed a novel decision-making paradigm inspired by influential studies of effort avoidance in the cognitive control domain (Kool et al., 2010)—which we termed the Decision Demand Task—to examine whether individuals, when given the choice, avoid choosing between high-demand risky choice pairs in favor of low-demand choice pairs. Finally, in Experiment 3, to understand the relationship between online effort exertion and demand avoidance in risky choice, we investigated pupillometric measures of online effort exertion while participants deliberated between risky choice pairs. Specifically, we examined task-evoked pupillary responses (TEPRs), which are demonstrated to index momentary cognitive effort exertion across diverse task domains (Beatty, 1982; da Silva Castanheira et al., 2021b; Fiedler & Glöckner, 2012; van der Wel & Steenbergen, 2018).We reasoned that high-demand choice pairs would evoke larger TEPRs on the basis of the increased effort these choice pairs presumably evoke, and that individuals who exerted more effort (as indexed by TEPRs) on high-demand choice pairs would also exhibit the strongest demand-avoidant preferences. Together, these experiments aim to extend our understanding of cognitive demand avoidance to the domain of value-based decision-making under risk.

Experiment 1

Methods

Participants

We recruited 37 adults (5 males, $M_{age} = 20.18$, standard deviation [*SD*] = 1.32) from McGill University's participant pool in exchange for course credits. Owing to a technical error, data of three participants failed to record properly. Of the 34 resulting participants, we further excluded the data from one participant who failed to choose the EV-maximizing option for the low-demand choices (see below) more than 60% of the time, resulting in a final sample of 33 participants. Participants provided informed consent and all procedures were in accordance with the McGill University's Research Ethics Board. 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 bonus amount: $5.00.

Risky decision-making task

Participants completed a risky decision-making task consisting of a series of choices between risky options (Fig. 1A), represented side-by-side, using pie charts to depict the possible outcomes and their associated probabilities (da Silva Castanheira et al., 2021a, 2021c; Guo et al., 2017). For example, participants would be asked to choose between an option with a 16% chance of winning $250 and an 84% chance of winning $355, or an option with a 35% chance of winning $611 and a 65% chance of winning $192. The pairs of pie charts representing risky prospects were depicted in one of two colors (red or blue) randomly selected on each trial, and importantly, this presentation color had no relationship with the demand level of the choice pair.[1]

Participants indicated their choice on each trial using the left and right arrow keys and had 5 s to make a response.

[1] We presented choice pairs using (noninformative) colors in Experiment 1 to assess whether choice pair presentation color biased demand ratings, because in Experiment 2, the demand level of a choice pair was conveyed by its (randomly assigned) presentation color. However, in Experiment 1, we observed no effect of presentation color (red versus blue) upon self-reported demand ($b = -0.05$, 95% CI [−0.13, −0.03], $p = 0.213$; Table 1), suggesting against the possibility that presentation color influenced subjective demand evaluations of choice pairs.

After a choice was made, the options were masked until the 5-s response window elapsed. Participants were not provided with outcome information after making each choice. After each choice, participants were either asked to rate how demanding the preceding choice was ("*How mentally demanding was that choice?*") following the NASA TLX scale (Hart, 2006), or how confident they felt in having made the best choice ("*How confident are you that the choice you made was the best choice?*") (Folke et al., 2016). Both ratings were collected on a 1–7 scale, with 1 indicating "not demanding"/"not confident" and 7 indicating "very demanding"/"very confident" using the number keys 1 through 7. Subjects completed 4 practice trials before choosing between (and subsequently rating) 200 presentations of choice pairs.

As part of our laboratory's standard data collection procedure, prior to the choice task, participants first completed two computerized tasks: the Digit Symbol Coding Task (Mathias et al., 2017) and the Operation Span task (OSPAN; Unsworth et al., 2005), which were not analyzed in the present study. Participants then completed a risky decision-making task. Following the choice task, participants responded to three questionnaires, which were also not analyzed in the present report: the Maximization scale (Nenkov et al., 2008), the Need for Cognition Scale (NFC; Cacioppo et al., 1984), and the State-Trait Anxiety Inventory (STAI; Spielberger, 1983).

Risky choice pair construction

We manipulated choice demand by altering the differences in expected values (EV) between the two options, defined as the average of an options' possible outcomes weighted by their associated probabilities (i.e., outcome magnitude multiplied by outcome probability), effectively creating two sets of 100 choice pairs each, defined by different levels of decision difficulty either low-demand (LD) or high-demand (HD). Specifically, low-demand choice differed markedly in EV (e.g., a 45% chance of $450 and $179 otherwise, EV:300.95; versus a 55% chance of $365 and $94 otherwise, EV:243.05), while high-demand choice pairs had similar EVs (e.g., an 84% chance of $355 and $250 otherwise, EV:338.2, versus a 35% chance of $611 and $192 otherwise, EV:338.65).

The complete lists of low-demand and high-demand choice pairs and the EVs of the constituent options are provided in Table S2 and S3, respectively. Critically, we constructed these sets of choice pairs such that the average EV (i.e., the mean EV of both options) did not differ appreciably across types of choice pairs, and so that the outcomes and risk levels (taken as the coefficient of variation; (Weber et al., 2004), as well the standard deviation of outcomes) associated to each option did not differ overall between low- and high-demand choice pairs. A statistical comparison of each choice pair attribute across low- and high-demand choice sets is provided in Table S1. Importantly, in both choice sets, the higher-EV option was equally likely to appear in the left and right position.

Finally, we also sought to ensure that low- and high-demand choice pairs, from the perspective of a decision-maker employing a purely heuristic strategy, would also engender the same levels of strategic conflict between simple heuristics. In particular, we considered two commonly used simple heuristic strategies: "maximin" and "maximax" (Pachur et al., 2017). The maximin heuristic prescribes choosing the option with the best of the worst possible outcomes, while the maximax heuristic prescribes choosing the option with the largest of the best possible outcomes. We constructed high-demand choice pairs such that the two heuristics would make conflicting prescriptions about choice. For example, faced with a (high-demand) choice between an 84% chance of $355 and $250 otherwise, or a 35% chance of $611 and $192 otherwise, the maximin heuristic would prescribe choosing the former option, while the maximax heuristic would prescribe choosing the latter. In contrast, we constructed low-demand choice pairs such that the two heuristics made concordant choice prescriptions—for example, faced with a (low-demand) choice between a 45% chance of $450 and $179 otherwise, or a 55% chance of $365 and $94 otherwise, both the maximin and the maximax heuristic would prescribe choosing the former option. In effect, under this operationalization of choice demand, the level of demand engendered by the EV discriminability of the options accords with the level of conflict generated by these two heuristics—that is, regardless of whether a decision-maker chooses on the basis of EVs versus simple heuristics, they would experience low and high levels of conflict in the low-demand and high-demand choice pairs, respectively. By equating these features of the two choice sets, we ensured against the possibility participants' evaluations of choice pairs would reflect only the level of difficulty (i.e., EV discriminability, or strategic conflict) and not the overall value or risk level associated with low- and high-demand choice pairs.

We constructed three different choice pair presentation orders (of 200 choice pairs each) by pseudo-randomly interleaving choice pairs from the 100 high-demand and 100 low-demand choice sets described above. Each participant was randomly assigned to one of these three presentation orders.

Data analysis

We used the lme4 package for R (Bates & Maechler, 2009) to estimate mixed-effects regressions examining the impact of choice demand level upon subjective demand and confidence. Specifically, these models predicted demand ratings

Table 1 Regression coefficients for mixed-effects regression predicting demand ratings in Experiment 1

Coefficient	Estimate	95% CI	*p*
Intercept	2.09	1.87–2.32	< 0.001
Demand level	1.87	1.47–2.27	< 0.001
RT (Z-scored)	0.21	0.11–0.31	< 0.001
Max. reward (Z-scored)	− 0.03	− 0.08–0.03	0.373
Presentation color	− 0.05	− 0.13–0.03	0.213
Run order (1)	0.19	− 0.20–0.58	0.339
Run order (2)	− 0.27	− 0.65–0.10	0.157
Run order (3)	− 0.12	− 0.52–0.27	0.534
Trail number (Z-scored)	− 0.09	− 0.16 – − 0.02	0.017
Demand * RT	0.25	0.16–0.34	< 0.001
Demand * Max. Reward	0.18	0.10–0.26	< 0.001

(or subjective confidence) as a function of dummy-coded task demand (hard = 1, easy = 0), choice response times (RTs) (Z-scored within-subject), as well as the interaction between RT and task demand. To control for potential effects of available reward on demand ratings and RTs (Shevlin et al., 2022), we included the maximum reward on offer (i.e., max of all four outcomes across options), Z-scored within-subjects, as well as the interaction between maximum available reward and demand level. We also assessed the effect of demand level on log-transformed choice RT by estimating a regression with the identical predictor variables. To analyze choices, we estimated a mixed-effects logistic regression predicting EV-maximizing choices as a function of demand level. In all regression models, we also estimated a linear effect of trial number (mean-centered), choice pair presentation color (red versus blue), as well as three dummy-coded variables representing that participant's stimulus presentation order. These models included random intercepts and random effects of demand level, taken over participants.

Results

Subjective demand and confidence ratings

We first assessed whether the demand level manipulation engendered different levels of subjective demand, as evinced by post-choice demand ratings (Fig. 1B). We observed that participants rated high-demand choice pairs ($M = 3.88$) as more demanding than the low-demand choice pairs ($M = 2.09$). This difference was confirmed statistically by a significant main effect of demand level upon demand ratings in a mixed-effects regression (b = 1.87, 95% confidence interval [CI] = [1.47, 2.27], $p < 0.001$; Table 1). We also assessed whether choice RTs predicted subsequent demand ratings and found a significant positive relationship (b = 0.21, 95% CI = [0.11, 0.31], $p < 0.001$), indicating that participants rated choices that they made more slowly as more demanding. This regression also revealed a significant positive interaction between choice demand level and RT (b = 0.25, 95% CI = [0.16, 0.34], $p < 0.001$), suggesting that choice slowing exerted a greater influence on subjective demand during high-demand (versus low-demand) choices.

Examining post-choice confidence ratings (Fig. 1C), participants reported feeling less confident after making a choice in a high-demand ($M = 4.52$) versus low-demand choice pair ($M = 6.11$). Statistically, a mixed-effects regression revealed a significant main effect of demand level (b = − 1.64, 95% CI = [− 1.89, − 1.40], $p < .001$; Table S4). We also assessed whether choice RTs predicted confidence ratings but did not observe a significant effect of RT (b = − 0.07, 95% CI = [− 0.17, 0.03], $p = .179$). However, demand level appeared to modulate the relationship between RT and confidence, such that the relationship between RT and confidence was stronger in high-demand choice pairs compared with low-demand pairs (interaction b = − 0.23, 95% CI = [− 0.32, − 0.14], $p < .001$).

Choices and response times

We expected that the difficulty inherent in high-demand choices, by virtue of the low EV discriminability (and/or heuristic conflict) between options, would result in slower decisions and lower-rates of EV-maximizing choices. Examining choice RTs (Fig. 2A), we observed that participants made slower choices in high-demand ($M = 5.02$ s) versus low-demand choice pairs ($M = 3.57$ s). This RT slowing was confirmed statistically by a mixed-effects regression, which revealed a main effect of demand level (b = 0.35, 95% CI = [0.27, 0.43], $p < .001$; Table 2). We also observed that participants made fewer EV-maximizing choices when faced with high-demand ($M = 0.47$) versus low-demand choice pairs ($M = 0.95$; Fig. 2B). Statistically, a logistic regression confirmed a significant effect of demand level upon of EV-maximizing choice rate (b = − 3.82, 95% CI = [− 4.05, − 3.58], $p < .001$; Table 3).

Discussion

Experiment 1 demonstrates that our operationalization of decision demand in the risky choice setting—which systematically manipulates EV discriminability while controlling for overall value, risk level, and differences in conflict between heuristics—successfully evoked different levels of subjective cognitive demand. Mirroring participants' self-reported demand ratings, we also observed that, when faced with high-demand choice pairs, participants made choices more slowly and fewer (optimal) EV-maximizing choices, suggesting that these choices engendered greater decision difficulty than low-demand choice pairs.

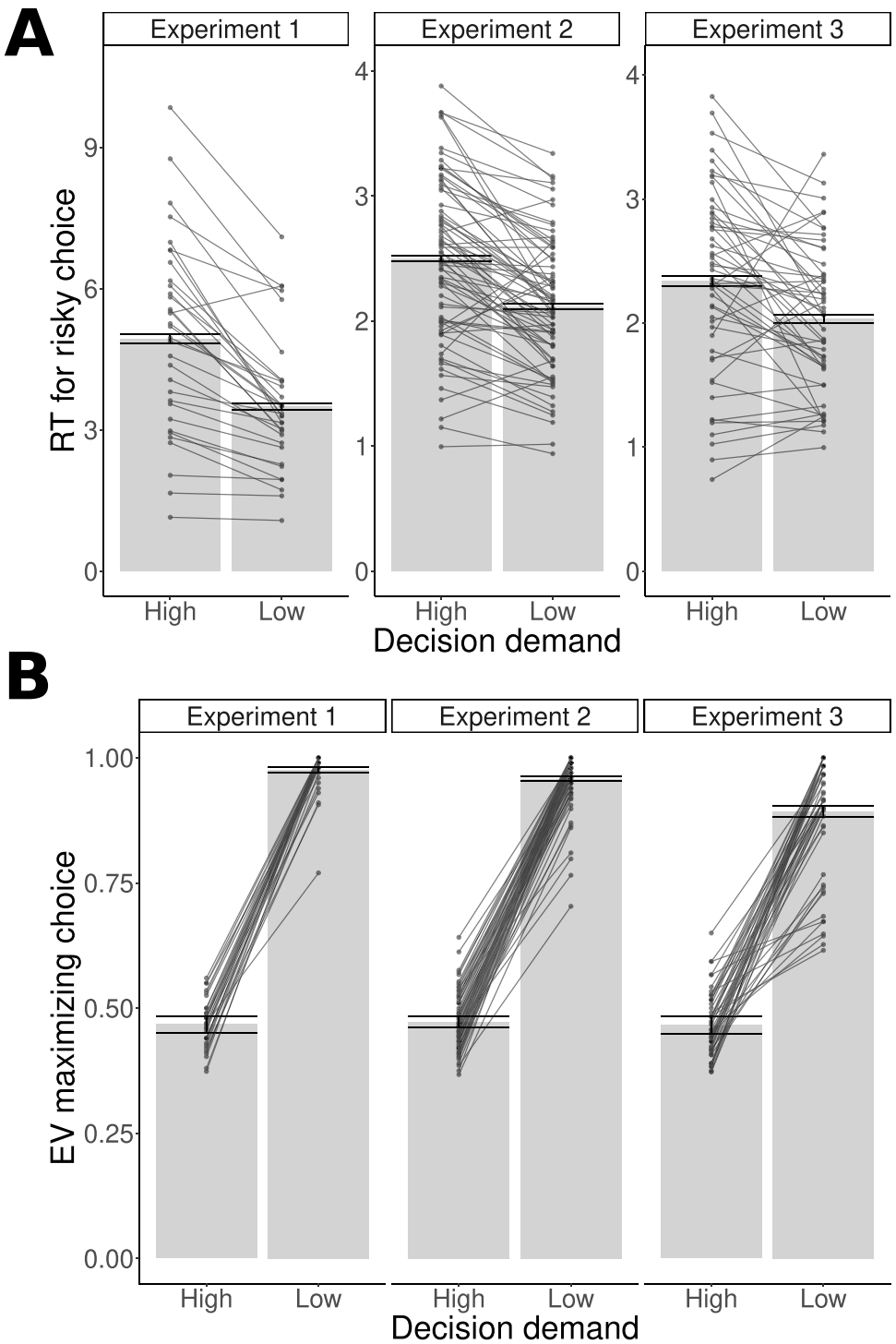

Fig. 2 Response times (RTs) and rates of expected value (EV)-maximizing choice for all three experiments. The dots and lines represent individual participants in each study. (**A**) Participants were also slower at responding when deciding between high-demand choices when compared with low-demand choices across all experiments. (**B**) Participants were more likely to select the EV-maximizing option for the low-demand over the high-demand choices across all experiments. Error bars represent standard error of the mean

Having established that our choice demand manipulation successfully evokes differential levels of subjective cognitive demand, Experiment 2 uses these same low- and high-demand choice pairs to examine whether individuals, when given the choice, tend to avoid high-demand risky choices. To examine this question, we developed a novel

Table 2 Regression coefficients for mixed-effects regression predicting choice RTs in Experiment 1

Coefficient	Estimate	95% CI	*p*
Intercept	1.08	0.94–1.22	< 0.001
Demand level	0.35	0.27–0.43	< 0.001
Max. reward (Z-scored)	0.02	0.01–0.03	0.004
Presentation color	−0.00	−0.02–0.02	0.766
Run order (1)	0.17	−0.07–0.41	0.174
Run order (2)	0.10	−0.13–0.33	0.407
Run order (3)	−0.28	−0.52 – −0.03	0.026
Trial number (Z-scored)	−0.07	−0.08 – −0.05	< 0.001
Demand * max. reward	−0.04	−0.06 – −0.03	< 0.001

Table 3 Regression coefficients for mixed-effects logistic regression predicting EV-maximizing choices in Experiment 1

Coefficient	*Log-Odds*	*95% CI*	*p-value*
Intercept	3.69	3.46–3.92	< 0.001
Demand level	−3.82	−4.05 – −3.58	< 0.001
Max. reward (Z-scored)	0.04	−0.19–0.26	0.738
Presentation color	0.05	−0.08–0.18	0.457
Run order (1)	0.03	−0.12–0.17	0.731
Run order (2)	0.05	−0.09–0.19	0.501
Run order (3)	−0.04	−0.19–0.10	0.579
Trail number (Z-scored)	0.05	−0.07–0.16	0.400
Demand level * max. reward	−0.01	−0.24–0.23	0.957

value-based paradigm based on the Demand Selection Task, which has been used examine cognitive demand avoidance in the domain of cognitive control (Kool et al., 2010). In Decision Demand Task (Fig. 3), participants first learned associations between two arbitrary stimuli and low- versus high-demand risky choice pairs (the Learning Phase), and following that, made free choices between these two stimuli (the Test Phase) which led to risky choice pairs with demand levels determined by the chosen stimulus. To the extent that individuals avoid cognitively demanding risky choices, as they do in cognitive control paradigms (Devine & Otto, 2022; Embrey et al., 2023; Kool et al., 2010; Sayalı & Badre, 2021), we expected to observe— on the basis of the subjective demand ratings and patterns of choice behavior in Experiment 1—that individuals would systematically avoid high-demand risky choices, in favor low-demand choice pairs.

Experiment 2

Method

Participants

We recruited 81 participants from McGill University's Psychology participant pool (20 males; 18–33 years; $M_{age} = 21.17$; $SD = 2.81$). We excluded data from two participants due to a technical error, and to ensure participants understood the choice task, we further excluded the data of three participants who failed to choose the EV maximizing choice on more than 60% trials for the low-demand stimuli during the Learning Phase, resulting in the exclusion of five participants.

Materials and procedure

As in Experiment 1, participants completed the Digit Symbol Coding and OSPAN tasks prior to the Decision Demand Task. In this paradigm (Fig. 3), participants first learned the associations between two distinct fractal stimuli and low- versus high-demand risky choice pairs (the Learning Phase), and subsequently made choices between these stimuli. Critically, one stimulus was deterministically associated with decisions from the low-demand set of choice pairs, while the other stimulus was associated with choice pairs drawn from the high-demand choice set (identical to those used in Experiment 1, see Table S2 and S3 for complete choice pairs). Mappings between stimulus and demand levels were counterbalanced across participants. The two task phases were separated by a self-paced break. Following the Decision Demand Task, participants completed the Maximization, NFC, and STAI questionnaires.

Learning phase

In the Learning phase of the Decision Demand Task, participants learned the deterministic mappings between the fractal stimuli and the associated choice pairs using a forced choice procedure. Specifically, on each trial, one stimulus was made transparent and participants were instructed to choose the more opaque stimulus. After choosing the instructed stimulus, choice, participants were presented with a choice pair consisting of two risky options and were required to make a subsequent choice. The mapping of choice pair presentation color (red versus blue) to demand level (low versus high) was randomized across participants. Before this phase began, participants were informed that the two fractal stimuli led to a different set of gambles and were instructed to pick the fractal stimulus leading to the set of gambles they preferred. Participants were told that when a fractal stimulus appears "grayed out," they would not be able to pick the that stimulus on that trial, and their job was to learn which types of gambles the two fractal stimuli lead to.

Critically, this choice pair was drawn either from the choice set (low- or high-demand) that was associated with

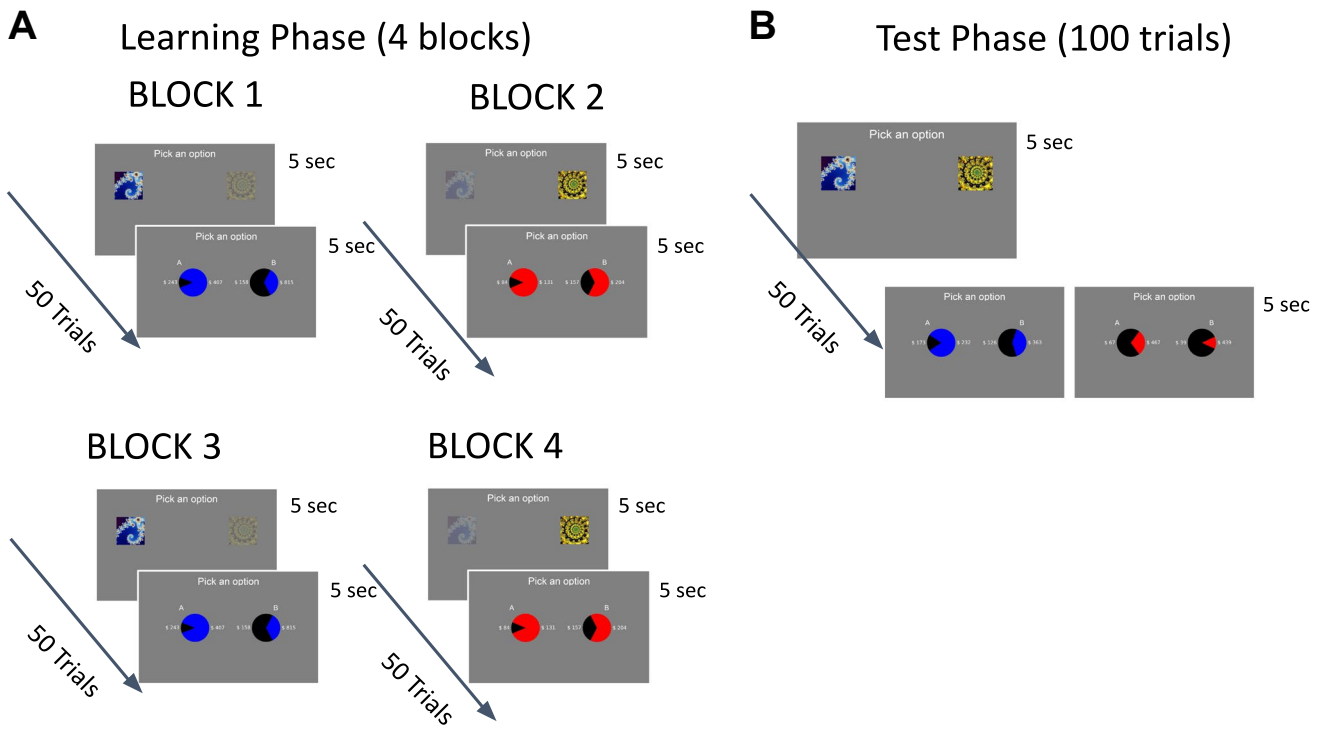

Fig. 3 Decision Demand Task used in Experiment 2. (**A**) In the Learning Phase, participants learned the demand levels of the choices pairs each stimulus (i.e., fractal) was associated with. Choices were offered between two risky options for whose outcomes and associated probabilities were depicted as pie charts. (**B**) In the Test Phase, participants were told to choose the stimulus associated with the set of choice pairs they preferred

the fractal stimulus that preceded the choice pair. Participants had 5 s to choose between fractal stimuli and 5 s to choose between each pair of risky options. The Learning Phase employed a blocked presentation order, such that participants performed 50 consecutive forced-choice trials with each stimulus (for a total of 200 trials over 4 blocks) with the order of blocks (defined by demand level) counterbalanced across participants. In effect, participants chose between every possible choice pair in the high- and low-demand choice sets in this phase, while learning its mapping to the associated fractal stimulus.

Test phase

Following the Learning Phase, participants completed the Test Phase, in which they made 100 free choices choose between the (previously learned) fractal stimuli. The Test Phase procedure was structurally identical to the Learning Phase procedure but with the key difference that, instead of making forced (i.e., instructed choices), participants could choose freely between the two stimuli. That is, following their choice of fractal, participants were presented with a choice pair randomly drawn from the low-demand choice pair set) or the high-demand choice pair set, depending on their choice, and participants were subsequently required to choose between the two risky options (presented in the associated color). In both the Learning and Test phases, Critically, participants were not provided with any instructions about demand levels associated with each stimulus, but rather, they were simply instructed to select the stimulus associated leading to choice pairs that they preferred.

Data analysis

We used mixed-effects regression to assess the effects of demand level upon risky choice RTs and rates of EV-maximizing choices in the Learning Phase (as this phased contained equal numbers of observations for each demand level). To examine demand preferences in the Test Phase, we estimated a mixed-effects logistic regression predicting selection of the high-demand stimulus on the basis of trial (i.e., choice) number, taking random intercepts over participants. Critically, the intercept term in this model was used to test for a reliable group-level preference for the low-demand stimulus. To examine individual differences, we estimated a separate model which additionally included participants' z-scored OSPAN, Digit Symbol, Maximization, Need for

Cognition, and OSPAN scores as covariates. These individual difference measures were not strongly correlated to each other (all rs < 0.30).

Results

Learning phase RTs and choices

We first examined choice behavior in the Learning Phase (Fig. 2), where participants were required to make an equal number of low- and high-demand choices. As in Experiment 1, we observed slower RTs (b = 0.17, 95% CI = [0.12, 0.21], p <.001), and lower rates EV-maximizing choice (b = − 3.38, 95% CI = [− 3.58, − 3.19], p <.001) indicating that, high-demand choice pairs were more difficult than low-demand choice pairs. Finally, we observed a significant positive correlation between a participant's median high-demand RT and their proportion of EV-maximizing choices (r =.255, p < 0.05; Fig. S1), indicating that participants who made choices more slowly on these trials were more able to make advantageous choices.

Demand avoidance in test phase choices

Our key question of interest in the Test Phase was whether individuals avoided demanding risky decisions—in other words, if participants systematically preferred the stimulus associated with low-demand choice pairs. Examining Test Phase preferences (Fig. 4), we found that participants had a marked preference for the stimulus associated with low-demand choice pairs, with the majority of participants choosing the high-demand option less than 50% of choices (median proportion of high-demand stimulus selections: 0.27). Statistically, this preference was confirmed by a significant negative intercept in our mixed-effects logistic regression model (b = − 1.7788, 95% CI = [− 2.26, − 1.29], p <.001), indicating that participants' preference for the low-demand stimulus was greater than would be expected by chance. We did not observe a significant effect of trial number (b = 0.0416, 95% CI = [− 0.06, 0.14], p = 0.423), suggesting that these demand-avoidant preferences were stable over the 100 trials of the Test Phase.

We also examined, in an exploratory fashion, whether individual differences in intrinsic motivation to engage in mentally effortful activities (Need for Cognition), working memory capacity (OSPAN), processing speed (digit symbol scores), and maximization predicted demand preferences. Estimating a separate logistic model, which included these individual difference variables as covariates (Table S5), we found that neither cognitive ability measure (processing speed or OSPAN, ps >.50) related to preference, nor did self-reported Need for Cognition or maximization tendency (ps >. 20) emerge as a predictor of high-demand choice.

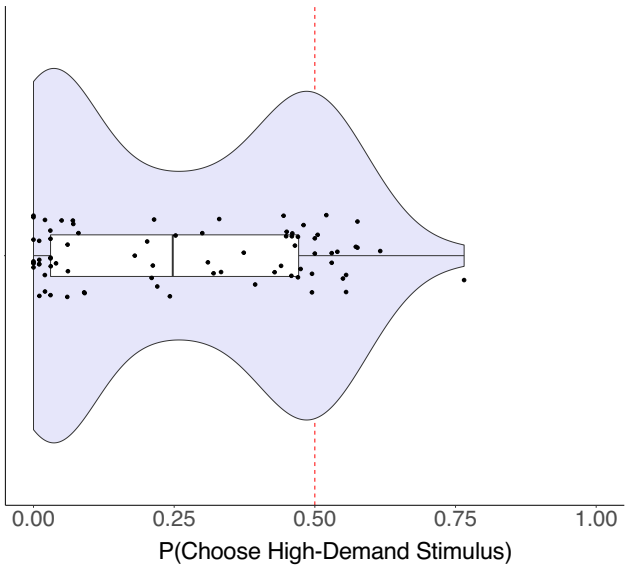

Fig. 4 Demand-avoidant preferences in the Test Phase of Experiment 2, depicted as a boxplot, superimposed over a violin plot depicting the distribution of each participant's proportion of high-demand stimulus selections. Each scatter point represents a single participant's proportion of high-demand stimulus selections. The dashed line represents chance (50%)

Finally, given the overall low rates of EV-maximizing choices on high-demand trials, we reasoned that it is possible that participants merely avoided these choice pairs, because they were unable make advantageous choices on these trials (rather than to avoid demand). To investigate this possibility, we examined Test Phase choices in 22 participants who made EV-maximizing choices on high-demand choices at a rate greater than 50% and found an overall preference of 36% for high-demand option (logistic regression intercept: b = − 0.885, p <.01), indicating significant demand-averse preferences in these participants. In short, the general demand avoidance effect observed here holds for participants who were able to make advantageous high-demand choices at above-chance rates.

Discussion

Building upon the considerable body of work demonstrating that people avoid demanding cognitive control tasks (Devine & Otto, 2022; Kool et al., 2010; Patzelt et al., 2019; Sayalı & Badre, 2021), the preferences we observed in the Test Phase of Experiment 2 suggest that individuals systematically avoid demanding risky choices. Because the overall (i.e., average) value and risk levels of high-demand and low-demand choice pairs were equated, these observed preferences are difficult to explain by preferences for valuable choice pairs or by risk aversion. Taken together with the findings of Experiment 1, these observed patterns of

preferences suggest that individuals, when given the choice, avoid decisions between options with low value discriminability (or heuristic conflict), which are experienced as subjectively demanding.

However, on the basis of the self-reported demand ratings observed in Experiment 1 and the demand preferences observed in Experiment 2, it is less clear how closely the subjective effort experienced during risky choice relates to demand avoidance. That is, while high-demand (versus low-demand) choice pairs presumably evoked different levels of cognitive demand, individual participants may vary considerably in the extent that they invested and/or experienced effort during these risky choices (Strobel et al., 2020; Westbrook & Braver, 2015). In a final experiment, we measured task-evoked pupil diameter changes—which have previously been demonstrated to track momentary effort exertion in the context of cognitive control tasks (Beatty, 1982; Chiew & Braver, 2013; da Silva Castanheira et al., 2021b; Kostandyan et al., 2019)—during the Decision Demand Task to better understand the relationship between online effort exertion during risky choices and subsequent demand-avoidant preferences. In doing so, Experiment 3 is positioned to elucidate two key questions. First, do task-evoked pupillary responses (TEPRs)—an index of momentary effort exertion— measured during risky choices in the Learning Phase track the respective demand levels of choice pairs? Second, with the assumption that individuals avoid choice pairs that evoke greater (subjective) effort, to what extent do individual differences in risky choice-evoked TEPRs predict subsequent demand-avoidant preferences in the Test Phase?

Experiment 3

Method

Participants

We recruited 81 participants (18 males, 2 nonbinary participants, 18–29 years, $M_{age} = 20.99$, $SD = 2.44$) recruited from the McGill University community for a base remuneration of $20 (CAD) or course credit with a performance-contingent cash bonus of up to $5. All participants were screened for corrected-to-normal, color blindness, and diagnoses of psychiatric or neurological conditions. We excluded those participants who failed 60% or more of the catch trials, those who failed to respond to more than 20% of trials, or those without usable pupil diameter measurements due to calibration issues or excessive eyeblinks. After applying these exclusions, 52 participants remained in the final sample.

Materials and procedures

Participants were seated comfortably in front of a 24-inch monitor set to a resolution of 1280 × 1024 pixels in a dimly lit room and instructed to keep their heads rested on a chin mount positioned 60 cm from the screen. During both phases of the Decision Demand Task, participants' left pupil diameter and fixations on the screen were 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 standard nine-point calibration procedure.

Decision demand task

Participants completed a version of the Decision Demand Task adapted for pupillometry recordings (Fig. 5). Like in Experiment 2, the task was broken into two phases: a Learning phase where they learned stimulus-choice set associations through forced-choice, and a test phase where participants freely chose among the stimuli. To eliminate possible differences in luminance stemming from the fractal and bar charts stimuli employed in Experiment 2, we opted to use two identical colored doors, represented as rectangles with identifying symbols (i.e., a five-point star or lightning bolt) in place of fractal stimuli. Participants had 2 s to decide between the doors, and following their choice, the door stimuli were masked until the 2-s response window elapsed. After this choice, participants were presented with a pair of risky options, now presented as stacked bar charts, following Tymula et al. (2012). These choices had a fixed duration of 5 s, with a visual mask applied after a choice was made. Following this, participants were presented a fixation cross which served as a jittered inter-trial interval between 2.5 to 3.5 s. To ensure participants could complete both phases of the task within a 2-h experimental session, we reduced the total number of Learning Phase trials from 200 to 120 in the Learning Phase (30 forced trials per block). Trials were organized into four Learning Phase blocks (2 of each demand level, following the blocked design of Experiment 2) and 2 Test Phase blocks (50 trials per block). Between blocks, participants were permitted to take short self-paced breaks.

Analysis of pupil diameter and eye movements

Pupillary data were preprocessed using the "pypillometry' package for Python (Mittner, 2020). Following downsampling of the pupillary timecourse data to 100 Hz, blinks were corrected using linear interpolation and the

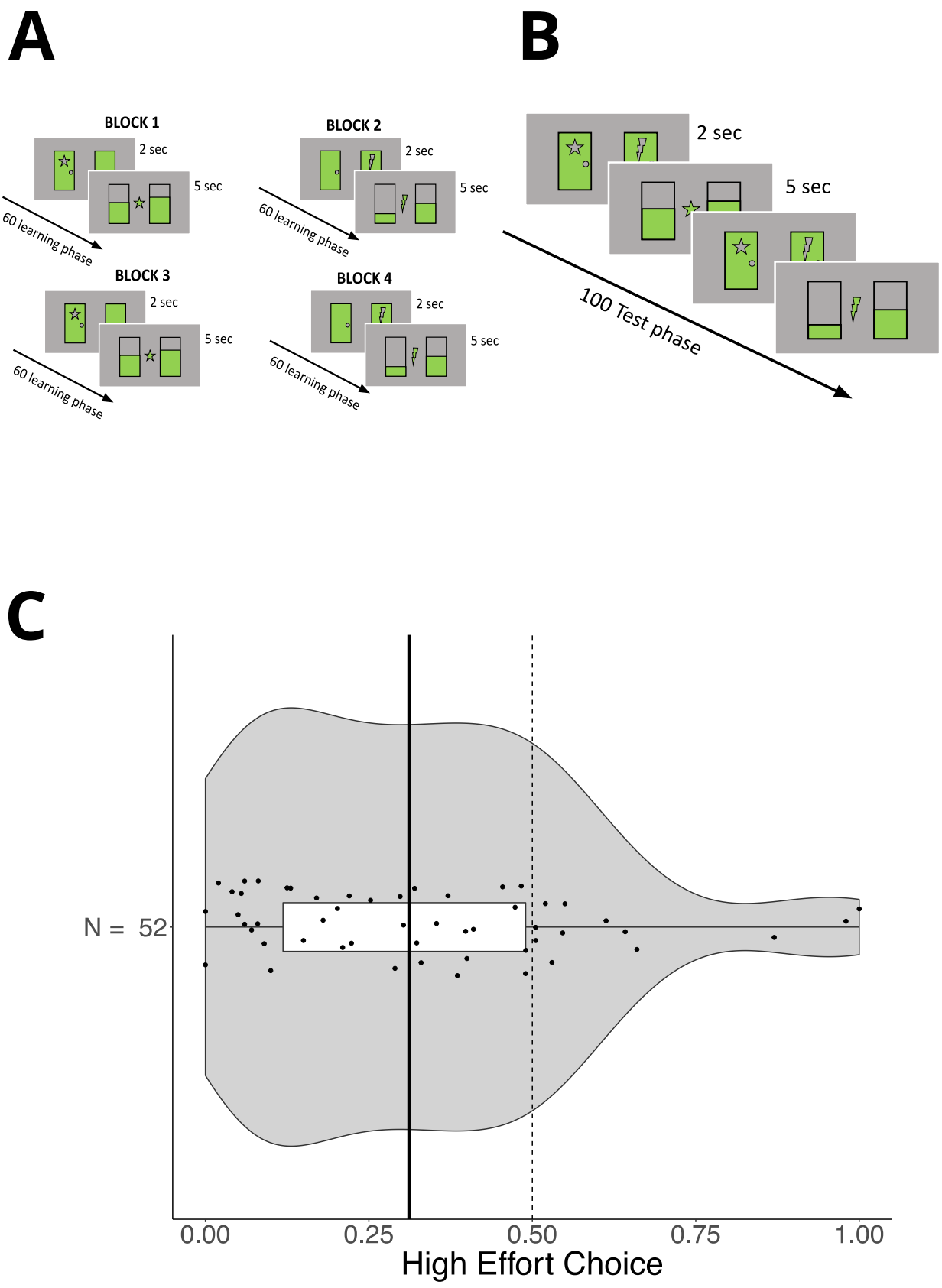

Fig. 5 (**A**) Learning Phase of the task in Experiment 3. (**B**) Test Phase of the task in Experiment 3. (**C**) Preferences for the high-demand stimulus the Test phase of Experiment 3

entire recording was passed through a low-pass filter, attenuating high-frequency signals above 1 Hz. Learning phase pupillary data were baseline-corrected on a trial-by-trial basis by subtracting the mean diameter of a 500 ms baseline period prior to stimulus presentation. Task-evoked pupillary responses were be calculated as the maximum (baseline-subtracted) pupil diameter, observed between 1,000 ms and 3,000 ms after choice pair onset, following previous work (da Silva Castanheira et al., 2021b; Gilzenrat et al., 2010). This time window of interest corresponds approximately to the median choice RT of 2.16 s observed in the Learning phase of Experiment 2.

We also analyzed gaze behavior during choices between risky options in the Learning phase. As with the pupillary data, the eye-position data (x and y pixel coordinates) were blink-corrected using linear interpolation and down-sampled to a frequency of 100 Hz. We defined two large areas of interest (AOIs) corresponding to each of the two risky options, with a margin of 100 pixels to the left and right of the choice stimuli, covering the entire height of the display (Fig. 5). We confirmed that these AOIs adequately captured fixations (and that participants were attending to the risky options), finding that overall, the vast majority participants' fixations were directed at either of the two options rather than elsewhere on the display (mean % of fixation in either AOI = 98.15%). We then computed, for each trial, the number of gaze shifts between these two AOIs before a choice was made (Folke et al., 2016) and the total Euclidean distance (in pixels) covered by the eye movements in the first second of the trial to capture both within-option and between-option shifts in attention.

Data analysis

Our analysis of choice behavior followed the procedure used in Experiment 2. To analyze trial-level TEPRs, we estimated a mixed-effects linear regression predicting Learning phase TEPRs as a function of the demand level of the choice pair, 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, taking random intercepts and slopes for demand level over participants. To examine individual differences in TEPRs, we computed participants' median TEPRs for the high- and low-demand choices in the Learning Phase and separately used these measures to predict subsequent demand avoidance in the Test Phase using mixed-effects logistic regression models. To analyze gaze patterns during risky choices in the Learning Phase, we estimated regressions predicting the number of gaze switches and the total distance covered (using Poisson and linear mixed-effects regressions, respectively) as a function of demand level, trial number, the total reward on offer, the outcome probabilities of the left and right options, and whether and an EV-maximizing choice was made. Finally, to analyze the predictive relationship between gaze displacements and advantageous choices, we estimated a mixed-effects regression predicting EV-maximizing choices as a function of trial number, demand condition (with low-demand serving as the reference level), total gaze displacement (z-scored within-subject), and the interaction of demand level and gaze displacement.

Results

Risky choice behavior and demand avoidance

Mirroring Experiments 1 and 2, we confirmed that participants made slower choices (b = 0.12, 95% CI = [0.05, 0.19], $p = 0.001$; Fig. 2A) and fewer-EV-maximizing choices (b = –3.40, 95% CI = [− 3.66, − 2.56], $p < .001$; Fig. 2B) on high- versus low-demand choice pairs. Further replicating Experiment 2, we observed in the Test Phase that participants significantly preferred the stimulus associated with low-demand choices (Fig. 5B), which was confirmed statistically by mixed-effects regression (intercept: b = − 0.97, 95% CI = [− 1.43, − 0.51], $p < 0.001$). Together, these results suggest the key behavioral signatures of cognitive demand in risky choice, and subsequent demand avoidance generalized replicate in a version of the Decision Demand Task adapted for pupillometry.

Learning phase task-evoked pupillary responses

To investigate whether our pupillometric index of effort investment tracked choice demand level during choice, we first examined TEPRs accompanying risky choices in the Learning Phase (Fig. 6A). We observed, rather unexpectedly, that TEPRs were larger accompanying low-demand choices versus high-demand choices. Examining these TEPR magnitudes in the time window of interest using a regression (Fig. 6B; see Methods), we observed a significant negative effect of choice demand level upon TEPR (b = − 61.52, 95% CI = [− 93.68, − 29.36], $p < 0.001$; Table S5). We also assessed whether average TEPRs accompanying low-demand trials was comparable between the Learning versus Test phases of the task but did not observe a significant difference between TEPRs in the two experiment phases (b = 38.60, 95% CI = [− 85.62, 8.42], $p = 0.108$). Owing to the blocked order of demand levels in the Learning phase, we examined baseline pupil diameter (the 500 ms period prior to choice pair onset) as a function of block demand level (Fig. 6D), observing that baseline pupil diameter was significantly larger on high- versus low-demand blocks (b = 90.90, 95% CI = [44.86, 136.94], $p < 0.001$), suggesting

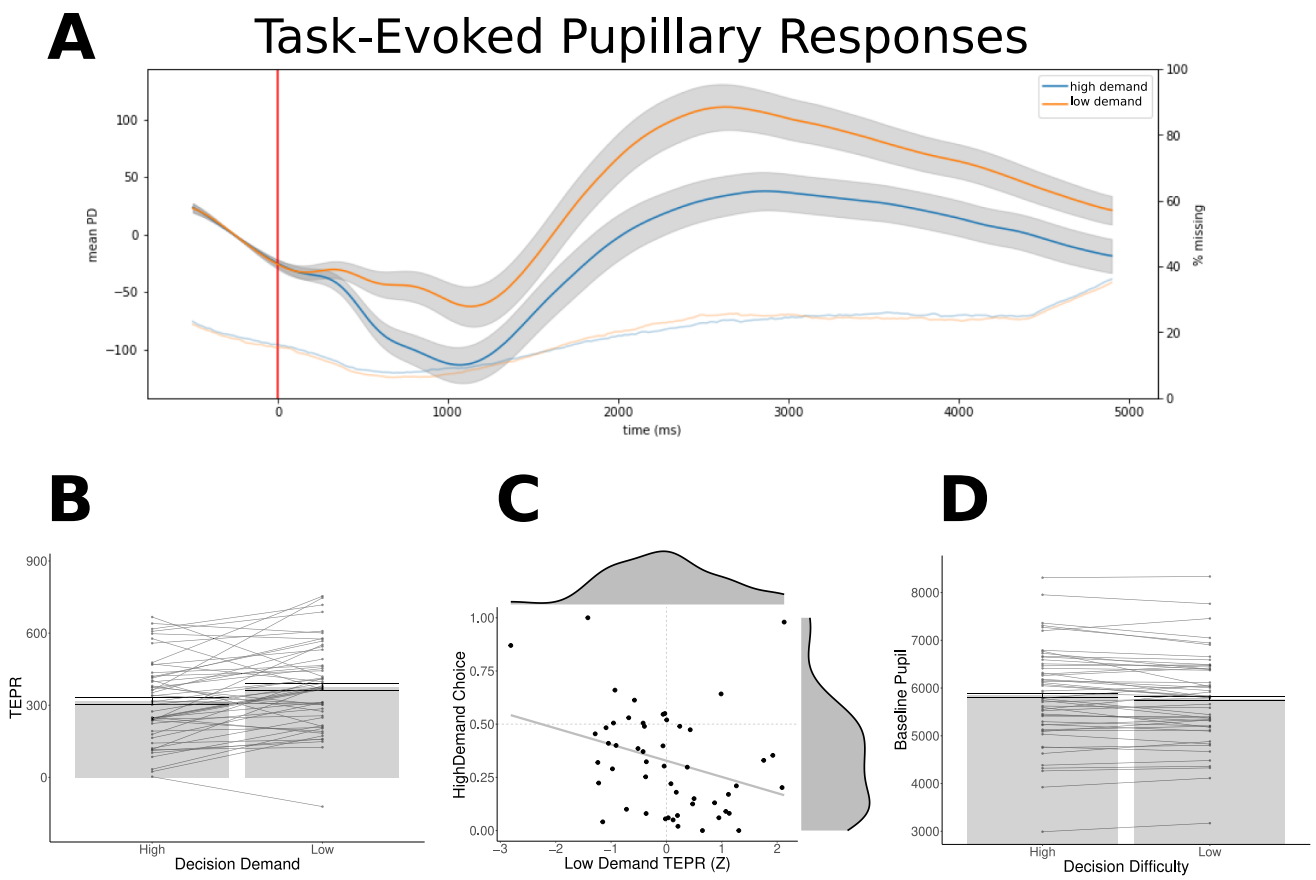

Fig. 6 (**A**) Time course plot of group-level task-evoked pupillary responses in the learning phase as a function of high- (blue) and low-demand (orange) choices, where stimulus onset is marked by a red vertical line. Faint blue and orange lines represent the proportion of missing observations due to blinks or other factors, demonstrating that there are no systematic differences between conditions with respect to the number of trials used to compute condition-level TEPRs. (**B**) TEPRs were significantly smaller accompanying high- versus low-demand choices in the Learning phase. (**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. TEPRs = task-evoked pupillary responses

a shift in tonic pupil diameter associated with decision demand.

We next examined the relationship between TEPRs measured during Learning phase choices—which we presume to index effort investment — and subsequent avoidance of high-demand choices in the Choice Phase. As we observed, unexpectedly, that low-demand choices evoked larger TEPRs than high-demand choices in the Learning Phase, we did not have a strong prediction about whether high- (versus low-demand) choice TEPRs in the Learning Phase would relate more strongly to subsequent demand avoidance in the Test Phase. Examining participant-level median TEPRs (Fig. 6C), we observed that TEPR magnitudes accompanying low-demand risky choices significantly predicted participants' subsequent preference for the low-demand stimulus ($b = -0.68$, 95% CI = [−1.33, −0.03], $p = 0.042$)—that is, individuals exhibiting larger TEPRs during low-demand choices in the Learning Phase chose the low-demand option more often frequently in the Test Phase. However, we did not find evidence for a predictive relationship between TEPRs accompanying high-demand risky choices and subsequent Test-phase preference for the low-demand stimulus ($b = 0.25$, 95% CI = [−0.40, 0.90], $p = 0.444$).

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 500 ms baseline period prior to stimulus onset. 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], $P < 0.001$), suggesting a shift in tonic pupil diameter associated with decision demand level.

Patterns of gaze during choice

We reasoned that the unexpectedly smaller TEPRs observed in high-, relative to low-demand choices might have arisen from a withdrawal of effort prompted by the high difficulty of these choice pairs stemming from low discriminability of EVs (Silvestrini et al., 2023). To directly address the possibility that participants invested less effort in the comparison of risky options on high-demand choices, we conducted an exploratory analysis of participants' patterns of gaze during Learning Phase choices, examining the frequency of shifts in gaze between the two options preceding choices (see example gaze trajectory depicted in Fig. 7A), which we took as a proxy for effortful information sampling (Folke et al., 2016; Horstmann et al., 2009). Accordingly, if participants are indeed withholding effort during high-demand choices, we reasoned that we should observe fewer shifts in gaze relative to low-demand choices.

Examining gazes shifts during Learning phase choices (Fig. 7B), we observed participants made an average of approximately two between-option gaze shifts during each choice, but more interestingly, these gaze shifts were less frequent during high-demand choices ($M = 2.14$) compared to low-demand trials ($M = 2.20$). Statistically, a mixed-effects Poisson regression indicated that participants shifted their gaze between options significantly less frequently during high-demand choices (demand level: $b = -0.06$, 95% CI $= [-0.12, -0.01]$, $p = 0.031$), suggesting that participants engaged in more (effortful) between-option comparison on low-demand, versus high-demand choices.

In a complementary analysis, we also computed the total Euclidian distance covered by eye movements during the first second of each trial, with the intuition that greater distance covered by eye movements in early choice periods reflects heightened information sampling. Corroborating the observed gaze shift frequencies, we observed that participants' total gaze displacements were smaller during

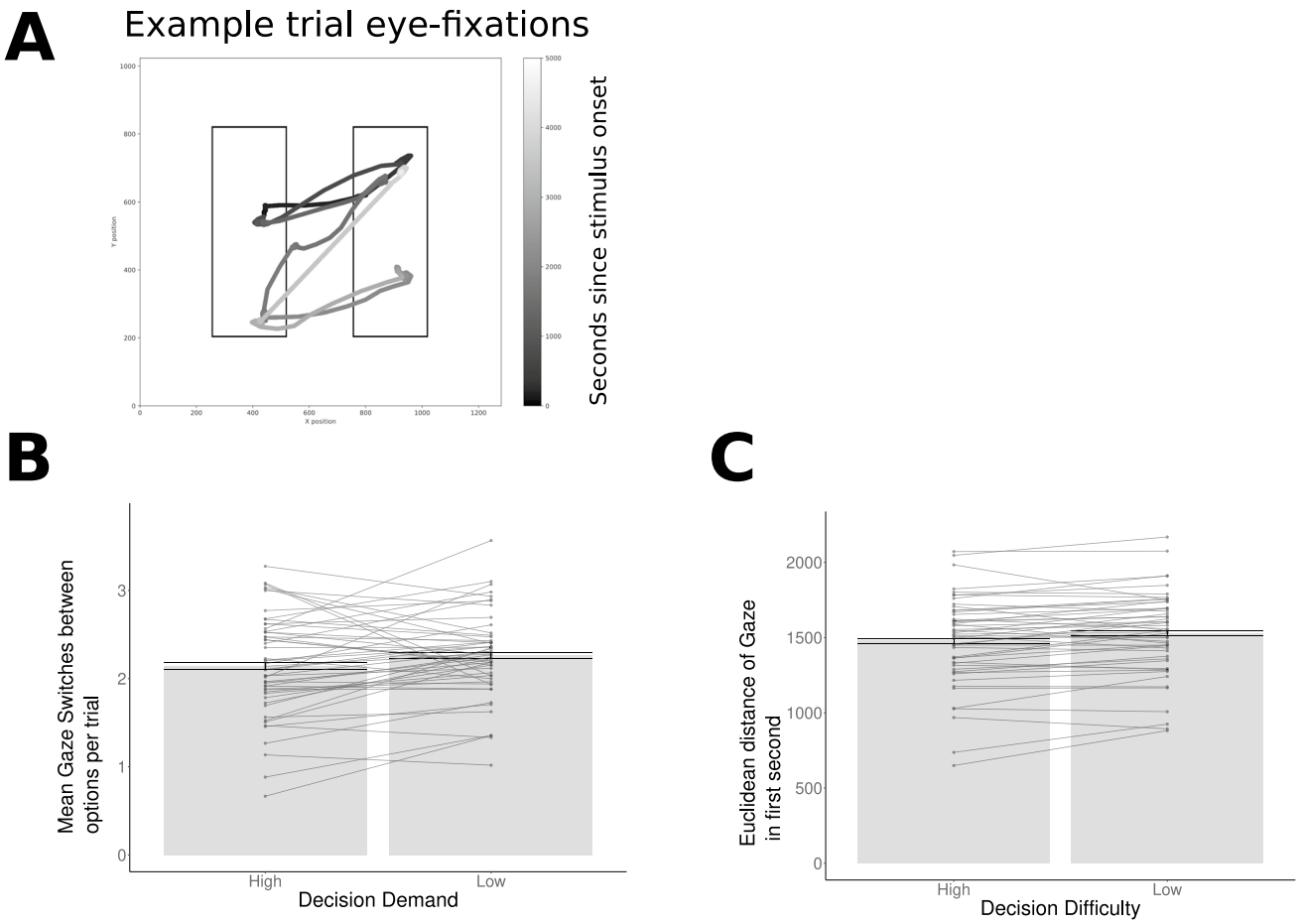

Fig. 7 (**A**) Example gaze trajectory on a Learning phase choice trial. Rectangles indicate the areas of interest where risky options (represented by the stacked bar charts) appeared on the screen. (**B**) Bar plot of the average number of gaze switches between the left and the right option per trial for both high- and low-demand choices. (**C**) Bar plot of the Euclidean distance of eye-fixations in the first second of the trial as a function of decision demand

high-demand, relative to low-demand choice pairs (Fig. 7C), and a mixed-effects linear regression confirmed this effect of demand level (b = −40.89, 95% CI = [−67.34, −14.44], $p < 0.001$). Finally, we examined whether total Euclidean distance covered (standardized within each demand level, for each participant) during individual choices predicted an EV-maximizing choice on that trial, and found that participants were more likely to make EV-maximizing choices on trials with larger gaze displacements (main effect of gaze displacement: b = 0.44, 95% CI = [0.27, 0.60], $p < 0.001$), during which participants presumably sampled more information about the risky options. This relationship was stronger on low-demand choices, as indicated by a significant interaction between Demand level and total distance covered (b = −0.41, 95% CI = [−0.60, −0.22]; $p < 0.001$; Table S6).

General discussion

The avoidance of cognitively effortful cognitive processing is a central assumption in many influential accounts of value-based decision-making (Gigerenzer & Gaissmaier, 2011; Payne et al., 1993; Shah & Oppenheimer, 2008). Taking an approach inspired by a recent body of work examining effort-based decision-making in cognitive control paradigms, we examine, in the domain of risky value-based decision-making, whether people similarly avoid cognitively demanding situations. Specifically, the experiments reported here demonstrate that 1) individuals' subjective, self-reported demand varies systematically with discriminability of the options' values (and/or conflict between heuristics), all else being equal, 2) when given the choice, individuals avoid choosing between these more subjectively demanding risky choices, and 3) a physiological index of effort investment during risky choice—namely, task-evoked pupillary responses—appears to predict individuals' subsequent preferences to avoid these more subjectively demanding risky choices.

Taken together, the present experiments provide an important demonstration of the generality of cognitive demand avoidance—which has been well characterized in paradigms where cognitive demand is operationalized in terms of cognitive control (Kool & Botvinick, 2018) and working memory (Vogel et al., 2020; Westbrook et al., 2013) demands—to the domain of risky value-based decision-making. The observation that individuals also systematically avoid risky choice situations for which evaluation and comparison of the options' values necessitates expenditure of cognitive effort, beyond expanding the scope of behaviors touched upon by cost–benefit accounts of effort-related decision-making (Shenhav et al., 2017), dovetails well with the influential idea that ostensibly suboptimal judgment and choice behavior stems from individuals' reluctance to engage in effortful deliberation processes (Gigerenzer & Gaissmaier, 2011; Shah & Oppenheimer, 2008).

Of note, we observed that participants in Experiments 2 and 3 exhibited a marked preference against high-demand risky choice pairs, which we operationalize as choice pairs for which discriminability between the EVs of the options is low (versus high). Importantly, our operationalization of choice demand anticipated the possibility that individuals might employ simple heuristics to choose between the pairs, rather than attempt to estimate EVs. As a result, the use of simplifying heuristics engendered conflict between risky options in high-demand choice pairs, presumably leading to the systematic differences in subjective demand between low- and high-demand choice pairs (observed in Experiment 1) and the systematic avoidance of these choice pairs (observed in Experiments 2 and 3).

Interestingly, we also observed in Experiment 1 that participants reported lower choice confidence following high-demand choices, compared to following low-demand choices. It is plausible that our operational definition of high demand—pairs of options with small EV differences—engendered low decision confidence as participants would conceivably be more uncertain (relative to when faced with low-demand choices) as to whether they made optimal, EV-maximizing choices when faced with these pairs. Indeed, the observed patterns of EV-maximizing choice across demand levels corroborate these confidence reports. In turn, it is possible that participants' apparent avoidance of these same choice pairs observed in Experiments 2 and 3 might stem, in part, from a desire to avoid a state of low decision confidence. Indeed, recent work demonstrates that individuals will engage in costly cognitive processing in order to increase decision confidence (Lee & Daunizeau, 2021), supporting the idea of a general prioritization of choice confidence.

In Experiment 3, we examined task-evoked pupil responses (TEPRs) accompanying risky choices to better understand effort investment on low- versus high-demand choice pairs during the Learning phase. Under the presumption that participants increase their level of effort investment in response to the demand level they encounter (here, in risky choice), we predicted that we would observe larger TEPRs— a marker of momentary effort exertion (da Silva Castanheira et al., 2021b; van der Wel & Steenbergen, 2018)—on high-demand choices. Somewhat surprisingly, we found that participants exhibited smaller TEPRs on high-demand, relative to low-demand choices suggesting that participants were withholding effort—relative to their effort investment level on low-demand choices—as they made these choices. Again, at the same time, participants in Experiment 1 rated these same high-demand choice pairs as more subjectively demanding.

One possible explanation for these patterns of TEPRs and subjective demand ratings is that participants perceive high-demand choice pairs as excessively difficult and accordingly, disengage (or withhold) effort on the assumption that increased decision effort yields little additional choice quality (Silvestrini et al., 2023). Indeed, this is a central tenet of Motivational Intensity Theory, which postulates that individuals invest effort when it yields a tangible benefit, but otherwise withhold effort (Brehm & Self, 1989; Gendolla et al., 2012) —for example, in the case of choices with low EV discriminability. On this view, we would expect higher demand ratings, but smaller TEPRs accompanying high-demand choices. Indeed, the apparent difficulty of making EV-maximizing choices we observed on these trials are not incompatible with an effort withdrawal interpretation. Difficulty discriminating between the options on the basis of EVs could have also prompted participants to make heuristic-based (rather than EV-based) evaluations of the options, which would not require participants to fully consider and/or utilize probability and/or outcome information. Examining participants' gaze patterns in Experiment 3, we found that participants' tendency to engage in between-option comparison—indexed by gaze shift frequency (Fig. 7B)—was lower for high-demand (versus low-demand) trials, corroborating the idea that participant disengaged from effortful choice processes on these trials, possibly in favor of simpler heuristics which do not take into all available outcome and probability information.

It is worth noting, however, that two observed patterns of results are difficult to explain under a simple effort withdrawal account. First, in all three experiments we observed slower choice RTs—typically interpreted as increased (effortful) deliberation between options (Bhui, 2019; Frömer & Shenhav, 2022)— on high- versus to low-demand choice pairs, whereas under an effort withdrawal account, we would expect to see faster choice RTs on trials for which participants disengaged. Second, it is not clear at first blush why individual differences in TEPRs on low-demand, but not high-demand, choices predicted subsequent avoidance of future high-demand risky choice pairs. One speculative possibility that is an individual's average TEPR on low-demand choices may reflect their general level of effort investment in risky choice (irrespective of choice demand level), which could predict subsequent avoidance of demand regardless of whether they engage effort in demanding situations—i.e., high-demand risky choice pairs. Under the assumption that high-demand choice pairs in this study were simply 'too difficult' owing to their low EV discriminability, future studies could test this disengagement account more comprehensively by examining self-reported demand, and TEPRs under a broader range of EV discriminability levels, including intermediate levels between the low- and high-demand discriminability levels examined here.

Another factor that may have plausibly influenced demand preferences is participants' potential awareness of the low efficacy with which they made high-demand choices, as evidenced by the low rates of EV-maximizing choices made on these trials. That is, if participants realize that, for these pairs, they are unlikely to make advantageous choices—owing to the low EV discriminability of the options—they might avoid these choice pairs, in part, because they cannot effectively increase their total payoffs by investing effort in these choices. While participants (in Experiment 1) rated high-demand choices as more demanding, which supports the idea that participants avoided choice pairs they experience as more cognitively demanding, it is possible their aversion to these choice pairs in Experiments 2 and 3 may have also stemmed from the low efficacy participants ascribed to these choice pairs. Viewed through the lens of influential cost–benefit accounts of effort expenditure, which prescribe that effortful mental processing should be engaged to the extent that the benefits of effortful processing outweigh its costs (Shenhav et al., 2013; Silvetti et al., 2018), we speculate that the apparent demand-avoidant choices observed here may arise from a cost–benefit evaluation. Specifically, because the costs (i.e., effort required to evaluate the EVs of the options) are large and the potential benefits (i.e., marginal increase in obtained payoffs with increasing effort) are small for high-demand choice pairs, participants may have avoided these pairs on account of their inferior (net) value of the effort these choices entail, relative to low-demand choice pairs. In other words, participants' demand preferences might stem from the (costly) effort involved in evaluating these options (as evidenced by subjective demand ratings), considered in light of the perceived benefit of these choice pairs, in accordance with this cost–benefit view. Further supporting this idea, we observed in Experiment 2 that participants who invested more effort in high-demand choices (as evinced by longer RTs) made more advantageous (i.e., EV-maximizing) choices.

Of note, previous theoretical accounts and neuroimaging studies delineate an important role for the dACC in representing relative cost–benefit effort evaluation, and in turn, mobilization of effortful cognitive processing directed by its presumed net benefit (Edgar et al., in press; Lopez-Gamundi et al., 2021; Shenhav et al., 2013; Silvestrini et al., 2023)—again, considered in the context of cognitive control paradigms—the present results suggest a role for this region in the evaluation of decision demand in risky decision-making. Possibly supporting this linkage, previous neuroimaging evidence finds evidence for a relationship between dACC activity and risky decision-making

(Brown & Alexander, 2017). At the same time, research has delineated a role for the dorsomedial PFC (dmPFC; which neighbors, or even overlaps functionally with the dACC) in in mobilizing effort in instrumental value-based choice (Clairis & Pessiglione, 2024) as well as representing control demands in multi-attribute decision-making (Venkatraman et al., 2009b).

Finally, the present results raise a number of open empirical questions. First, while this investigation focused on value-based choices with uncertain outcomes (i.e., risky choices), we reason that any value-based choice domain, could, in principle, produce the same patterns of self-reported demand and demand-avoidant preferences. For example, intertemporal choices—whereby individuals choose, for example, between $1 today versus $2 in 1 week—are well-characterized by subjective value functions (Green & Myerson, 2004) and the similarity of competing options' subjective values has been used previously to instantiate choice difficulty in this context (Jimura et al., 2018; Pine et al., 2009). Similarly, in choosing between consumer products with rated values, individuals experienced choices between high-valued (but not low-valued) items with similar subjective values as more anxiety-inducing, suggesting that, if given a choice, individuals would also seek to avoid these choices (Shenhav & Buckner, 2014). Thus, it would be worthwhile to examine the generality of observed demand avoidance in other types of value-based choices. Second, while participants' preferences generally favored the low-demand choice pairs in the test phases of Experiments 2 and 3, we still observed considerable individual variability in these preferences, suggesting that not participants may have been aware of the different demand levels associated with the two stimuli. It would be useful to test, in future studies, participants' explicit knowledge of these demand levels—and how this knowledge relates to choices—following previous approaches investigating demand avoidance in the domain of cognitive control (Bogdanov et al., 2022a; Gold et al., 2015).

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Authors' contributions KSC conceived of the initial research question, designed, and programmed all experiments, analysed data, and drafted the manuscript. A.R.O. supervised all stages of the project, secured funding, and edited the manuscript.

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Data availability All raw data pertaining to this study can be accessed via the Open Science Framework at https://osf.io/h235v.

Declarations

Conflicts of interest/Competing interests The authors have no relevant financial or nonfinancial interests to disclose.

Ethics approval Approval was obtained from the McGill University Research Ethics Board. The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Consent to participate/Consent for publication Informed consent was obtained from all individual participants included in the study. Participants signed informed consent regarding publishing their data.

Open Practices Statement Raw data for these studies are publicly available at https://osf.io/h235v/.

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