Short-term memory capacity predicts willingness to expend cognitive effort for reward

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Author Note

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Abstract

We must often decide whether the effort required for a task is worth the reward. Past rodent work suggests that willingness to deploy cognitive effort can be driven by individual differences in perceived reward value, depression, or chronic stress. However, many factors driving cognitive effort deployment - such as short-term memory ability - cannot easily be captured in rodents. Furthermore, we do not fully understand how individual differences in short-term memory ability, depression, chronic stress, and reward sensitivity impact cognitive effort deployment for reward. Here, we examined whether these factors predict cognitive effort deployment for higher reward in an online visual short-term memory task. Undergraduate participants were grouped into high and low effort groups ($n_{\text{HighEffort}} = 348$, $n_{\text{LowEffort}} = 81$; $n_{\text{Female}} = 332$, $n_{\text{Male}} = 92$, $M_{\text{Age}} = 20.37$, $Range_{\text{Age}} = 16\text{-}42$) based on decisions in this task. After completing a monetary incentive task to measure reward sensitivity, participants completed short-term memory task trials where they could choose to encode either fewer (low effort/reward) or more (high effort/reward) squares before reporting whether or not the colour of a target square matched the square previously in that location. We found that only greater short-term memory ability predicted whether participants chose a much higher proportion of high vs. low effort trials. Drift diffusion modeling showed that high effort group participants were more biased than low effort group participants towards selecting high effort trials. Our findings highlight the role of individual differences in cognitive effort ability in explaining cognitive effort deployment choices.

Keywords: cognitive effort, working memory, chronic stress

Word count: 7374

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Significance statement

We must often make decisions about when cognitive effort is worth the potential reward. Reward value, depression, and chronic stress in rodents can impact cognitive effort deployment decisions for reward, but factors like short-term memory ability can only be easily characterized in humans. We examined whether short-term memory ability, depression, chronic stress, and reward sensitivity predict cognitive effort decisions for reward. In a short-term visual memory task with a choice of easier or harder trials for low vs. high reward, we found that only short-term memory ability predicted more choices of high vs. low effort trials. This research suggests that cognitive effort decisions could be driven by cognitive effort ability more than motivational factors like depression or chronic stress.

Introduction

We are often faced with difficult choices about work and life. For example, we may choose to spend time thoroughly studying for an exam to gain a few extra percent points on a grade; alternatively, we may trade off this reward to work less and be able to do other tasks. These choices require trading off more or less effort for a larger or smaller reward, and thus involve deciding how much cognitive effort to deploy. In general, the motivation to deploy cognitive effort can be influenced by the potential reward to be gained (Shenhav, Botvinick, & Cohen, 2013; Shenhav, Cohen, & Botvinick, 2016; Yee, Crawford, Lamichhane, & Braver, 2021). Beyond this, an individual's willingness to expend cognitive effort can also be linked to individual differences in factors that influence overall motivation, such as mood disorder levels (Grahek, Shenhav, Musslick, Krebs, & Koster, 2019; Pruessner, Barnow, Holt, Joormann, & Schulze, 2020; Yee, Adams, Beck, & Braver, 2019). Research in rodents has revealed patterns of individual differences in motivation to

exert cognitive effort, where rats are classified as “workers” (high effort group) or “slackers” (low effort group) depending on whether they are willing to work more or less for reward, respectively (Hosking, Cocker, & Winstanley, 2016; Silveira, Wittekindt, Ebsary, & Winstanley, 2021; Silveira, Wittekindt, Mortazavi, Hathaway, & Winstanley, 2020). However, factors influencing individual differences in willingness to deploy cognitive effort for reward have yet to be fully characterized in humans.

In both rodents and humans, chronic stress (Birn, Roeber, & Pollak, 2017; Watt, Weber, Davies, & Forster, 2017) and depressive traits (Grahek et al., 2019; Silveira et al., 2020) have been shown to negatively impact cognitive effort deployment for reward. In rodents, chronic stress dampens reward sensitivity even as acute stress heightens it (Ironside, Kumar, Kang, & Pizzagalli, 2018; Kúkel’ová et al., 2018). Here, chronic stress is typically induced by prolonged social defeat (Kúkel’ová et al., 2018) or non-social chronic mild stress, such as modifications to housing (Slattery & Cryan, 2017). In humans, chronic stress - unlike acute stress - cannot ethically be induced. Research into the impact of chronic stress on reward motivation primarily focuses on reports early childhood stress (Birn et al., 2017; Watt et al., 2017), and not shorter-term chronic stress of the kind that university students may experience (Towbes & Cohen, 1996). This latter form of chronic stress is more widely experienced than early childhood stress, and yet its impact on our willingness and ability to complete everyday cognitive tasks is not well understood.

Alongside chronic stress, depression is another motivational factor that has been shown to dampen reward sensitivity (Terpstra et al., 2023; A. Westbrook et al., 2020; S. R. Westbrook, Hankosky, Dwyer, & Gulley, 2018). In particular, anhedonia - a key symptom of depression impacting interpretations of reward (Slattery & Cryan, 2017) - can drive reduced reward sensitivity and negatively impact willingness to deploy effort in rodents (Scheggi, De Montis, & Gambarana, 2018). Similarly, in humans, trait-level anhedonia (Treadway, Bossaller, Shelton, & Zald, 2012; Treadway, Buckholtz, Schwartzman, Lambert,

& Zald, 2009) and anticipation of anhedonia (Sherdell, Waugh, & Gotlib, 2012) generally predicts reduced motivation to deploy physical effort for reward (Culbreth, Moran, & Barch, 2018). However, many tasks in life are cognitive as opposed to physical in nature; cognitive effort tasks may offer more naturalistic value as a result.

Cognitive factors influencing willingness to deploy cognitive effort in humans are more complex than those that we can evaluate with rodents (Stephan, Volkmann, & Rossner, 2019). Humans require less training than rodents on cognitive effort tasks, and can be evaluated on a greater variety of behavioural measures that may reveal factors influencing individual differences in willingness and ability to deploy cognitive effort for reward. For example, even if we are highly motivated to exert cognitive effort, reduced executive function capability could drive increased reliance on reward incentives - leading us to deploy cognitive effort beyond our capabilities and increasing the risk of failure (Kool, McGuire, Rosen, & Botvinick, 2010; Sandra & Otto, 2018). One executive process that we use in everyday life is visuospatial working memory, or the ability to hold in mind and manipulate object locations in space. Increased working memory ability can in turn drive improved attentional control - an aspect of cognitive effort - while reduced working memory ability is associated with poorer control (Unsworth & Robison, 2020). Furthermore, during cognitively effortful tasks, reward sensitivity modulates activation in neural circuitry that supports working memory (Fuentes-Claramonte et al., 2015).

The *Expected Value of Control* theory (Shenhav et al., 2013) predicts that, in general, people will deploy more cognitive effort when they know that they can effectively obtain greater rewards while doing so (Frömer, Lin, Dean Wolf, Inzlicht, & Shenhav, 2021). Additionally, the theory predicts that greater reward anticipation will lead to higher expected value of deploying cognitive effort to obtain a reward (Grahek, Musslick, & Shenhav, 2020). However, the degree to which individual differences in reward sensitivity and executive function capacity influence the likelihood of choosing to deploy more

cognitive effort for higher reward is not known.

In rodents, different levels of motivation between ‘workers’ and ‘slackers’ have also been associated with differences in learning rate and bias towards choosing high effort trials, and that this may be linked to differences in cognitive capacity. Drift diffusion modeling in rodents completing a cognitive effort task has revealed that ‘workers’ with high accuracy may accumulate evidence more quickly towards selecting high effort, high reward trials than ‘slackers’ or ‘workers’ with low accuracy (Hales et al., 2024). Overall, the above findings suggest that effort cost computations interact with reward sensitivity as factors we rely on to make judgments about the value of deploying more or less cognitive effort for reward. In turn, individual differences in reward sensitivity may be linked to depressive traits or chronic stress, and rodent research indicates that executive capacity may also influence choice behavior (Eichenbaum, 2017). The goal of the present study was to examine the degree to which individual differences in reward sensitivity, chronic stress levels, and depressive traits on the one hand, and visuospatial short-term memory as an index of executive function on the other, predict human choice behaviour independently or in interaction.

The present study

One way of examining factors that motivate humans to deploy more or less effort for reward is to offer participants the choice of completing an easier or harder cognitive effort task for a low or high reward, respectively (Treadway et al., 2009). In the current study, we built on an existing rodent choice task to investigate whether visual short-term memory capacity, chronic stress, depressive traits, and reward sensitivity predict one’s choices in deploying cognitive effort for reward. We adapted the rodent Cognitive Effort Task (rCET) (Cocker, Hosking, Benoit, & Winstanley, 2012; Hosking et al., 2016; Silveira et al., 2020) for use in humans. In the rodent paradigm, rodents first learn to associate illuminated lights with the opportunity to obtain a reward. In the main phase of the task, rodents are

given the choice between a low effort, low reward (LR) trial or a high effort, high reward (HR) trial. Then, in a basic memory task, they must poke their noses in a hole that lights up for either 1000 ms (LR) or 200 ms (HR) (Cocker et al., 2012). Rodents must rapidly encode the location of the illuminated light to succeed. Such a task can be scaled up to human working memory capabilities by including more stimuli and features that must be encoded to obtain a reward. For our study, we used harder and easier conditions (smaller vs. larger set size) from a visual short-term memory task (Luck & Vogel, 1997) to serve as high and low cognitive effort choices within the same kind of choice paradigm offered in the rCET. In each trial, participants could choose to perform an easier visual short-term memory task for a lower reward or a harder task for a higher reward. We examined overall visuospatial short-term memory capacity as well as indices of depressive traits (Beck, Steer, & Brown, 1996), chronic stress (Levenstein et al., 1993), anhedonia (Rizvi et al., 2015), and reward sensitivity (Terpstra et al., 2023) as predictors of the tendency to choose lower or higher effort tasks. Furthermore, we used drift diffusion modeling (Hales et al., 2024; Ratcliff, 1978) to examine factors that may contribute to choice biases.

Materials and Methods

Participants

Table 1

Demographic information for all participants, by sex and effort deployment group. BDI prop = Beck Depression Inventory II proportion score (score divided by max score). PSS = Perceived Stress Scale score. DARS = Dimensional Anhedonia Rating Scale. Ant. = mean reward anticipation in the behavioural monetary incentive delay task. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected.

Group	*Sex*	*n*	M_{age}	SD_{age}	Min_{age}	Max_{age}	$M_{BDIprop}$	$SD_{BDIprop}$	M_{PSS}	SD_{PSS}	M_{DARS}	SD_{DARS}	$M_{ant.}$	$SD_{ant.}$
High effort	Female	263	20.34	2.37	16	42	0.27	0.18	20.83	6.21	35.61	11.71	3.94	1.81
	Male	80	20.70	2.34	17	32	0.19	0.14	17.69	5.30	37.69	9.62	4.29	1.75
	Other	5	20.40	0.89	19	21	0.17	0.10	19.60	3.65	43.00	10.07	4.80	1.64
Low effort	Female	69	20.01	1.94	16	26	0.28	0.16	20.68	6.54	38.04	8.94	4.00	1.79
	Male	12	20.92	2.97	18	28	0.19	0.14	21.08	4.38	39.17	8.61	3.96	1.51

We powered our study using a power analysis through the `pwrss` package (Bulus, 2023) to achieve an expected power of 80% at an odds ratio of 0.70 for a logistic regression

evaluating the probability of a participant selecting 70% or more high effort trials (being in the high effort group in the study). This analysis gave us a target sample size of $N = 487$. We recruited $N = 570$ participants from the Human Subject Pool of psychology undergraduate students at the University of British Columbia; they were each compensated with bonus points for their courses as well as a CAD $5.00 Starbucks gift card. Of these, $n = 42$ participants did not complete the initial survey and $n = 7$ participants did not complete the reward anticipation task. Furthermore, $n = 11$ participants completed the change detection task more than once, $n = 2$ participants spent more than 30 seconds choosing any one trial - as this could indicate disengagement with task demands, and $n = 79$ participants performed at or below chance (50%) during the choice phase of the task. In total, we analyzed data from $N = 429$ participants ($n = 92$ male, $n = 332$ female, $n = 5$ other; Table 1). The study was approved by the Behavioural Research Ethics Board at the University of British Columbia, ethics code H20-01388.

Stimulus Presentation

All participants completed the study online on their own devices, via the Pavlovia online study platform using PsychoPy 2021.2.3 (RRID: SCR_006571) (Peirce et al., 2019). Participants were not allowed to complete the study on mobile phones or tablets.

Stimuli

All stimuli used in the study were generated by and implemented in PsychoPy (Peirce et al., 2019). In the first phase of the study, participants performed an online behavioural monetary incentive delay task as a measure of reward sensitivity (Fig. 1A) as outlined in Terpstra et al. (2023). In brief, during this initial task phase, participants saw a series of scales that they could click to indicate how excited they were to receive a reward. After a brief wait, participants would see a small happy face appear on one side of the screen. Afterwards, they were shown whether they received a reward or not, and were

asked to view another scale where they would indicate how excited they felt. They completed this task for a series of eight trials.

In the second phase of the study, as a measure of each individual's visuospatial short-term memory capacity we presented a visuospatial short-term memory task (Fig. 1B, C) modified from Luck and Vogel (1997) and adapted from an open-source version of the task on Pavlovia (de Oliveira, João Roberto Ventura, 2023). In this task, we presented a series of trials with between 2 and 8 coloured squares that were presented for 500 ms. Each square subtended a visual angle of approximately 0.05° on the screen. A mask with multi-coloured squares would then appear at each of the original squares' locations for another 500 ms, followed by a single coloured square appearing in one of the positions of the original squares. This final square had a 50% chance of being the same or a different colour from the square appearing in the same position in the initial part of the trial. After indicating with a keyboard press whether the square was the same or a different colour from the initial square, they would see whether or not they gained points towards a monetary reward.

Procedure

Questionnaires and monetary incentive delay task

Participants began the study by completing an online questionnaire. After giving consent and demographic information, they were asked how about their history of depression and anxiety; COVID-related stress; the Perceived Stress Scale (PSS; Levenstein et al. (1993)); the Beck Depression Inventory II (BDI; Beck et al. (1996)); and the Dimensional Anhedonia Rating Scale (DARS; Rizvi et al. (2015)). Afterwards, they were redirected to the first phase of our study, the online behavioural monetary incentive delay task (Fig. 1A; Terpstra et al. (2023)). This task measured participants' reward sensitivity via the mean of the excitement ratings given before each trial.

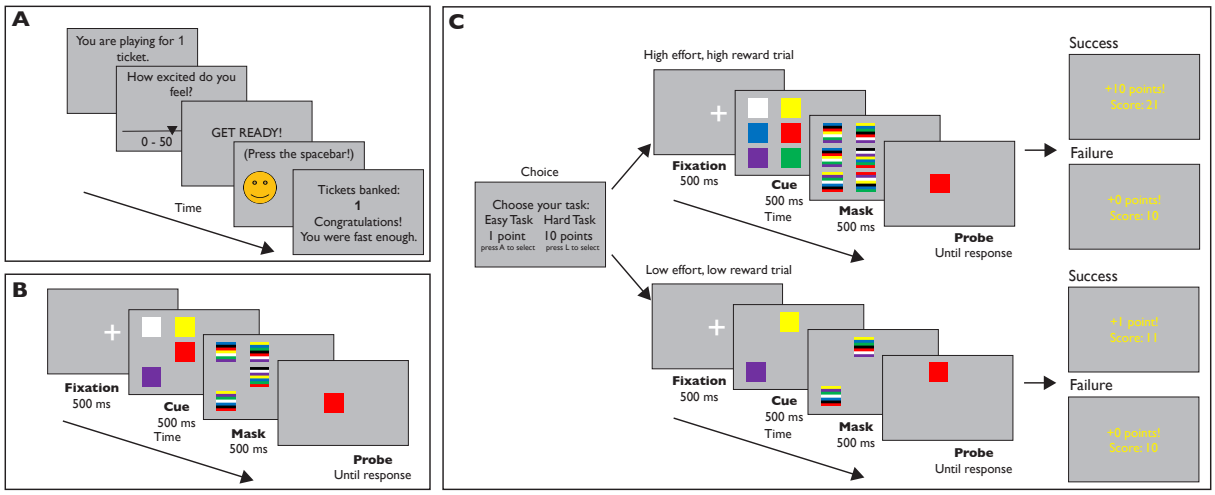

Figure 1

Layout of the experimental tasks. (A) The Monetary Incentive Delay Task, in which participants indicate their excitement in playing for tickets towards a monetary reward.(B) The calibration phase of the change detection task, where participants saw an array of either 2, 4, 6, or 8 squares and indicated whether the final square that appeared (the probe) was of the same or a different colour from the square that appeared in the same location in the previously show array. (C) The reward phase of the change detection task, where participants saw an array of either 2 or 4, or 6 or 8, shapes on screen depending on their performance in the calibration phase of the task. Once again, participants indicated with a keyboard press whether the final square that appeared (the probe) is the same or a different colour from the square that appeared in the same location in the array. Here, if they made the correct decision, they would receive 1 point (low effort trial) or 10 points (high effort trial); they would receive 0 points for an incorrect decision.

Visuospatial short-term memory task

Versions of this task served both as a means to measure individual differences in visuospatial short-term memory as well as the tasks of varied cognitive effort to be subsequently chosen for high/low effort trials. After completing the monetary incentive delay task, participants were redirected to the second phase of our study, the visuospatial short-term memory task (Luck & Vogel, 1997). Here, this task served as a means to measure individual differences in visuospatial short-term memory as an index of working memory. After receiving instructions on which stimuli would appear and how to respond to them, participants first completed a series of ten practice trials presented in a random order. On half of these trials, the probe square was the same colour as that of the cue square (congruent/change trial); on the other half, the probe square was a different colour

from that of the cue square (incongruent/no change trial). Of these practice trials, four had a set size = 2, another four had a set size = 4, and another two had a set size = 6. In each trial the probe square could be anywhere in the array, and participants were required to hold the whole array in visual short-term memory in order to successfully indicate whether the probe color had changed. Participants did not receive feedback on whether their responses were correct or not in the practice block, in keeping with Luck and Vogel (1997). Following these practice trials, participants completed (Fig. 1B) a series of 120 trials of the visuospatial short-term memory task with 60 change and 60 no change trials. In total, 30 trials of each set size (2, 4, 6, and 8 squares onscreen) were presented in a randomized order. Although the original task by Luck and Vogel (1997) contained trials with up to 10 squares onscreen, this largest set size was determined to be too difficult for participants to reliably complete correctly following piloting; as such, the maximum set size was 8.

Based on participants' performance in this phase of the task, a K estimate of their visuospatial working memory capability (Rouder, Morey, Morey, & Cowan, 2011) was calculated for each set size, as follows:

$$\hat{k}_p = N\left(\frac{\hat{h} - \hat{f}}{1 - \hat{f}}\right)$$

where N is the set size, $\hat{h}$ is the hit rate, and $\hat{f}$ is the false alarm rate. Although our task was a single-probe recognition task, we used the initially proposed whole-display K estimate measure (Pashler, 1988) to ensure a stricter criterion than the single-probe K estimate measure. The whole-display K estimate measure has also previously been used in single-probe change detection tasks (Rouder et al., 2011).

In addition to serving as indices of individual differences in visuospatial short-term memory, K estimate scores were used to calibrate the tasks used in the effort choice task

(Fig. 1C), which was based on the rodent cognitive effort task (Hosking et al., 2016; Silveira et al., 2021). Here, participants completed a series of 30 trials. They would receive rewards for making a correct response, and they could choose a high effort, high reward (HR) trial or a low effort, low reward (LR) trial at each trial. Importantly in this task, trials with small and large arrays from the visuospatial short-term memory task served as the LR and HR trials. HR trials used a larger set size, but gave a reward of 10 points towards a monetary reward. LR trials had a smaller set size than the high effort/high reward trials, but yielded a reward of 1 point towards a monetary reward. In order to ensure that the task difficulty in this phase was balanced by participants' working memory capability, we used participants' K estimate score at set size = 4 from the initially-presented visuospatial short-term memory task - the last set size before performance began to drop off - to set a criterion for the available set sizes in HR and LR trials. Specifically, if the K estimate at set size 4 was <= 3, participants could choose an LR trial with a set size of 2 or an HR trial with a set size of 6. If the K estimate at set size 4 was > 3, participants could choose an LR trial with a set size of 4 or an HR trial with a set size of 8. Although participants were told that the the number of points they gained in this phase was proportion to the monetary reward they would receive, all participants received the same reward (a $5 CAD Starbucks gift card) at the end of the study. Afterwards, participants were redirected to a debriefing survey and received their course credit and monetary reward.

Analyses

All analyses were conducted using R 4.3.1 "Beagle Scouts" (R Development Core Team, 2011) through RStudio (Booth et al., 2018).

The primary predictor variables in our study were 1) working memory ability, operationalized as a participant's K estimate at a set size of 4; 2) depressive traits, operationalized as a participant's BDI proportion score; 3) chronic stress levels, operationalized as a participant's PSS score; and 4) reward sensitivity, operationalized as a

participant's mean excitement before playing for tickets in the monetary incentive delay task (Terpstra et al., 2023). As our overall depression score measures were of more translational interest than anhedonia, given the role of depression in downweighing effort deployment and reward anticipation in both rodents (Slattery & Cryan, 2017) and humans (Grahek et al., 2019), we focus on reporting this measure as opposed to the anhedonia measure we also collected. The primary dependent variable in our study was 1) proportion of HR trials chosen in the reward phase of the task; operationalized as whether participants chose the HR option for more or less than 70% of all trials in the reward phase. We further examined 2) accuracy, operationalized as the proportion of correct responses (hits and correct rejections) in the effort choice (reward) phase of the task and 3) choice latency, operationalized as the time in seconds until participants selected a difficulty level on each trial in the effort choice phase of the task. Finally, drift diffusion model parameters of drift rate, starting point, boundary separation, and non-decision time (Hales et al., 2024) during choices in the effort choice (reward) phase of the task were additional outcome variables. To evaluate whether participant motivation to choose high effort trials for high reward significantly explained performance (accuracy in the reward phase of the task) and choice latency (time until participants selected a difficulty level in the reward phase), we classified participants into two categories according to the criteria discussed in Silveira et al. (2021): participants who chose the HR option for more than 70% of all trials in the reward phase were in the *high effort preference group*, while participants who chose the HR option for less than or equal to 70% of all trials in the reward phase were in the *low effort preference group*. This grouping was chosen to ensure continuity with comparable cognitive effort studies in rodents (Hales et al., 2024; Hosking et al., 2016; Silveira et al., 2021).

For our analyses, we first conducted a series of t-tests to evaluate sex differences in BDI and PSS scores. Past work suggests sex differences in depressive traits (Altemus, Sarvaiya, & Neill Epperson, 2014; Forys et al., 2023) and chronic stress levels (Watt et al., 2017), with women presenting with higher depression and chronic stress scores than men.

For sex difference comparisons, only male and female participants were included as we were under-powered to report sex differences from those reporting sex as "other". Next, we divided participants into high and low effort groups to ensure translational comparability with existing rodent work. As in Cocker et al. (2012), participants who chose the HR option for more than 70% of all trials in the reward phase of the task were in the *high effort preference group*, while those who chose the HR option for 70% or less of all trials in this phase were in the *low effort preference group*. We first conducted a binomial linear regression to determine whether sex, working memory ability, depressive traits, chronic stress levels, and reward anticipation significantly predicted whether a participant was in the high or low effort group in terms of their effort choices. We then conducted two 2x2 within-between ANOVAs (Trial type x Group) using `anova_test` through the `rstatix` package (Kassambara, 2023) to evaluate whether accuracy or choice latency significantly differed by trial effort level (HR vs. LR) and motivation group (high effort vs. low effort groups). We examined accuracy and choice latency to evaluate whether participants were matched for performance and time spent selecting a trial (Cocker et al., 2012), regardless of how many high vs. low effort trials they selected. We then ran two multi-level models through the `lmerTest` package (Kuznetsova, Brockhoff, & Christensen, 2017) to evaluate whether sex, working memory ability, depressive traits, chronic stress levels, reward anticipation, and effort level significantly predict choice latency or accuracy. Lastly, in order to evaluate whether the high and low effort groups differed in response strategies and biases towards selecting HR vs. LR trials, we fit a hierarchical Bayesian drift diffusion model, adapted from Ratcliff (1978) and run for 2000 iterations with 1000 warmup iterations and 4 Markov chains for Monte Carlo sampling, to data from all participants using the `hBayesDM` package in R (Ahn, Haines, & Zhang, 2017). We used this model to compare drift rate, starting point, boundary separation, and non-decision time between participants who chose high levels of effort vs. those who chose low levels of effort. The drift rate captures the rate at which participants drift towards a decision boundary

(selecting an HR or LR trial). The starting point captures the initial bias, at the beginning of each trial, that participants have towards selecting an HR over an LR trial. The boundary separation captures a trade off between speed and selecting the HR trial as opposed to the LR trial. Lastly, non-decision time captures the part of choice latency that is not related to cognitive effort decisions, such as the time required to execute a motor response upon making a decision.

Results

Depressive traits and chronic stress levels

Summary statistics for depressive traits (BDI) and chronic stress levels (PSS) can be found in Table 1. After correcting for multiple comparisons using the Bonferroni method, women had significantly higher depressive trait scores ($t(261.23) = 5.35$, $p =$ <0.001, $d = 0.45$) (Fig. 2A) and chronic stress scores ($t(270.03) = 4.93$, $p <0.001$, $d =$ 0.40) than men (Fig. 2B). However, men and women did not significantly differ on anhedonia scores ($t(253.79) = -2.05$, $p = 0.373$, $d = -0.17$) (Fig. 2C) or levels of mean reward anticipation ($t(233.53) = -2.50$, $p = 0.118$, $d = -0.23$) (Fig. 2D).

Predictors of overall high vs. low effort choices

Our primary research question focused on factors that predict the likelihood of choosing high vs low effort/reward options (Table 2; Fig. 3). Here, results of the binomial regression showed that only visuospatial working memory (K estimate) score significantly predicted whether a participant was in the high effort or the low effort group ($z = 2.26$, p $= 0.024$, $e^{\beta} = 1.24$). Participants with higher working memory ability had a higher probability of being in the high effort group. Sex, depressive traits, chronic stress levels, and reward anticipation did not significantly predict whether participants were in the low vs. high effort groups.

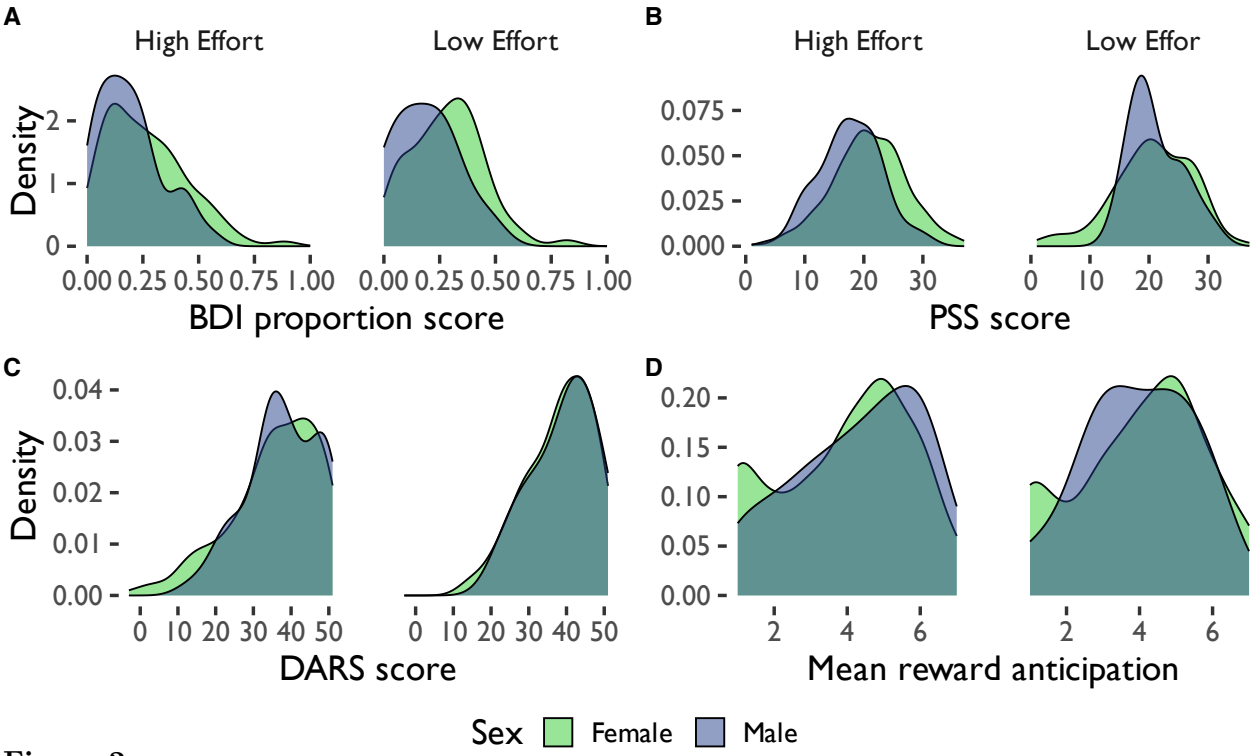

Figure 2

Distribution of (A) depressive trait (BDI) proportion scores (score divided by total possible score), (B) perceived stress (PSS) scores, (C) anhedonia (DARS) scores, and (D) mean reward anticipation scores by sex. BDI = Beck Depression Inventory, PSS = Perceived Stress Scale, DARS = Dimensional Anhedonia Rating Scale.

Accuracy

In all ANOVAs reported below all p-values were corrected for multiple comparisons using Greenhouse-Geiser correction. A 2x2 within-between ANOVA (Group x Trial Type; Fig. 4A) revealed a main effect of Trial Type on accuracy such that participants showed poorer performance on the more difficult HR trials compared to the easier LR trials ($F(1, 273) = 724.10$, $p < 0.001$, $\gamma = 0.515$). This was qualified by a Trial Type x Group interaction such that participants in the high effort group performed better than those in the low effort group on LR but not HR trials ($F(1, 273) = 11.81$, $p < 0.001$, $\gamma = 0.017$).

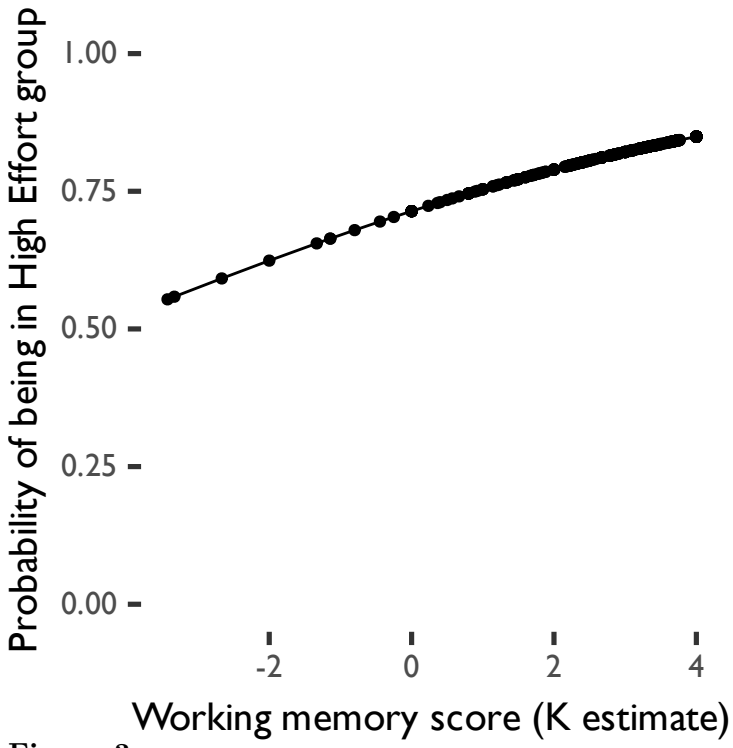

Figure 3

Binomial logistic regression predicting whether participants were in the high effort vs. low effort group. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected.

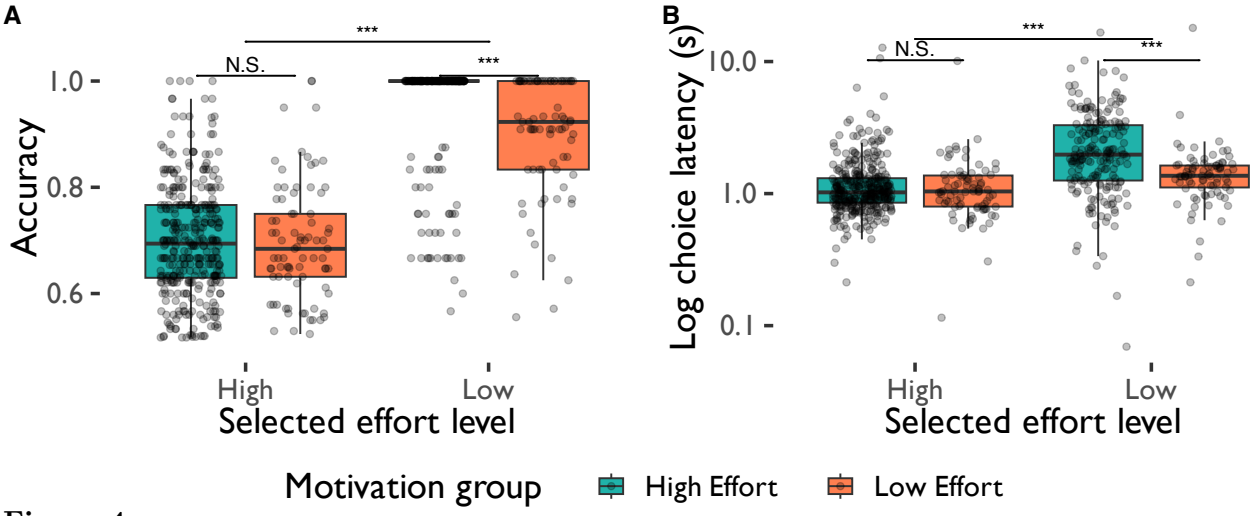

Figure 4

Accuracy and choice latency in the choice phase of the change detection task by motivation group (high effort vs. low effort group). The choice latency plot has been log-transformed on the y-axis to more clearly show small choice latency values. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected.

Table 2

Binomial logistic regression predicting whether participants were in the high effort vs. low effort group. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected. BDI (prop. score) = depression score on the Beck Depression Inventory, PSS = Perceived Stress Scale. Proportion scores are scores divided by total possible score. AIC = Akaike information criterion, BIC = Bayesian information criterion, ICC = intraclass correlation, RMSE = root mean squared error.

	Binomial logistic regression: High vs. low effort group
(Intercept)	1.14+
	(0.60)
Working memory ability (K estimate)	0.21*
	(0.09)
BDI (prop. score)	−0.78
	(0.96)
PSS	0.00
	(0.03)
Reward anticipation	0.00
	(0.07)
Num.Obs.	429
AIC	419.7
BIC	440.0
Log.Lik.	−204.833
RMSE	0.39

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Choice latency

A 2x2 within-between ANOVA (Group x Trial Type; Fig. 4B) revealed a main effect of Group such that participants were slower to choose HR trials compared to LR trials ($F(1, 273) = 37.50$), p <0.001, $\gamma = 0.063$). Furthermore, high effort participants were slower than low effort participants to make choices across all trial types ($F(1, 273) = 10.10$), $p = 0.002$, $\gamma = 0.019$). There was also an Trial Type x Group interaction, such that participants in the high effort group took longer to select LR trials than HR trials, while choice latency between high effort and low effort groups did not differ on HR trials ($F(1, 273) = 37.50$), p <0.001, $\gamma = 0.021$).

Additional predictors of accuracy and choice latency

We additionally evaluated predictors of accuracy and choice latency from individual differences in participant visuospatial short-term memory capacity, mood disorder score, and reward sensitivity by sex. A multi-level model analysis revealed that the effort level required in the selected trial significantly predicted accuracy across all trials such that accuracy was higher on low effort (LR) trials compared to high effort (HR) trials. Importantly, of the predictors of interest, only visuospatial short-term memory score predicted acccuracy, such that higher short-term memory ability was associated with higher accuracy (Table 3; Fig. 5A). Trial effort level also predicted choice latency, with slower choices on low relative to high effort trials. Depression scores also predicted choice latency such that higher depression scores predicted faster choices across all trials (Table 4; Fig. 5B) Sex, chronic stress scores, and reward anticipation did not significantly predict accuracy or choice latency.

Drift diffusion model

To evaluate group differences in evidence accumulation and bias towards deploying higher amounts of cognitive effort in decision making when choosing HR or LR trials, we fit a hierarchical Bayesian drift diffusion model (Ahn et al., 2017) to choice (HR vs. LR trial selected) and corresponding choice latency data on each trial from all participants who had at least one correct response on an HR and an LR trial ($N = 136$, $n_{Higheffort} = 94$, $n_{Loweffort} = 42$). We then evaluated this overall model fitting data from these participants to explore group-level differences in whether participants selected HR or LR trials more often. For each participant in the high effort and low effort groups, we evaluated four parameters: drift rate (speed of evidence accumulation in deciding on an HR vs. LR trial), starting point (bias towards HR vs. LR trial), boundary separation (extent to which speed and effort choice are traded off between HR and LR trials), and non-decision time (portion of choice latency time unrelated to trial choice, such as time for motor response) (Fig. 6).

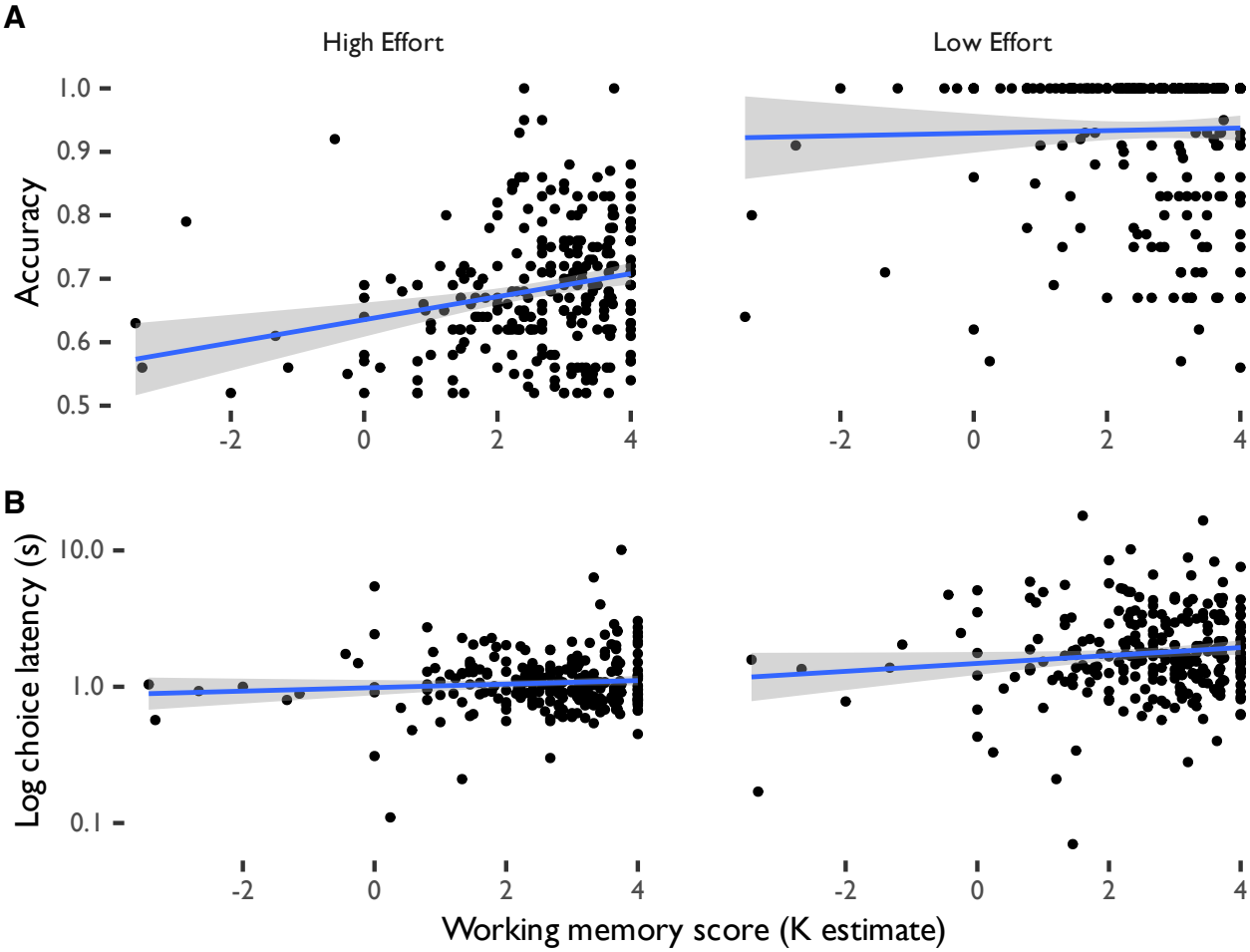

Figure 5

(A) Accuracy and (B) choice latency in the reward phase of the change detection task by working memory ability (K estimate). The choice latency plot has been log-transformed on the y-axis to more clearly show small choice latency values.

These parameters capture individual differences in the speed and motivation to make a decision about deploying more or less cognitive effort for reward. After Bonferroni correction for multiple comparisons, we found that high effort group participants had a starting point closer to the HR trial decision boundary ($t(71.58) = 3.81$, $p = 0.003$, $d = 0.74$) and had wider decision boundaries ($t(68.92) = 4.40$, $p <0.001$, $d = 0.87$) than low effort group participants. However, high and low effort group participants did not significantly differ in drift rate ($t(78) = 1.88$, $p = 0.58$, $d = 0.35$) or in non-decision time ($t(106.11) = 2.17$, $p = 0.29$, $d = 0.36$). These findings suggest that participants who were in the high effort group required more evidence to select high effort trials, and were more

strongly biased towards selecting high effort/high reward trials, than those in the low effort group.

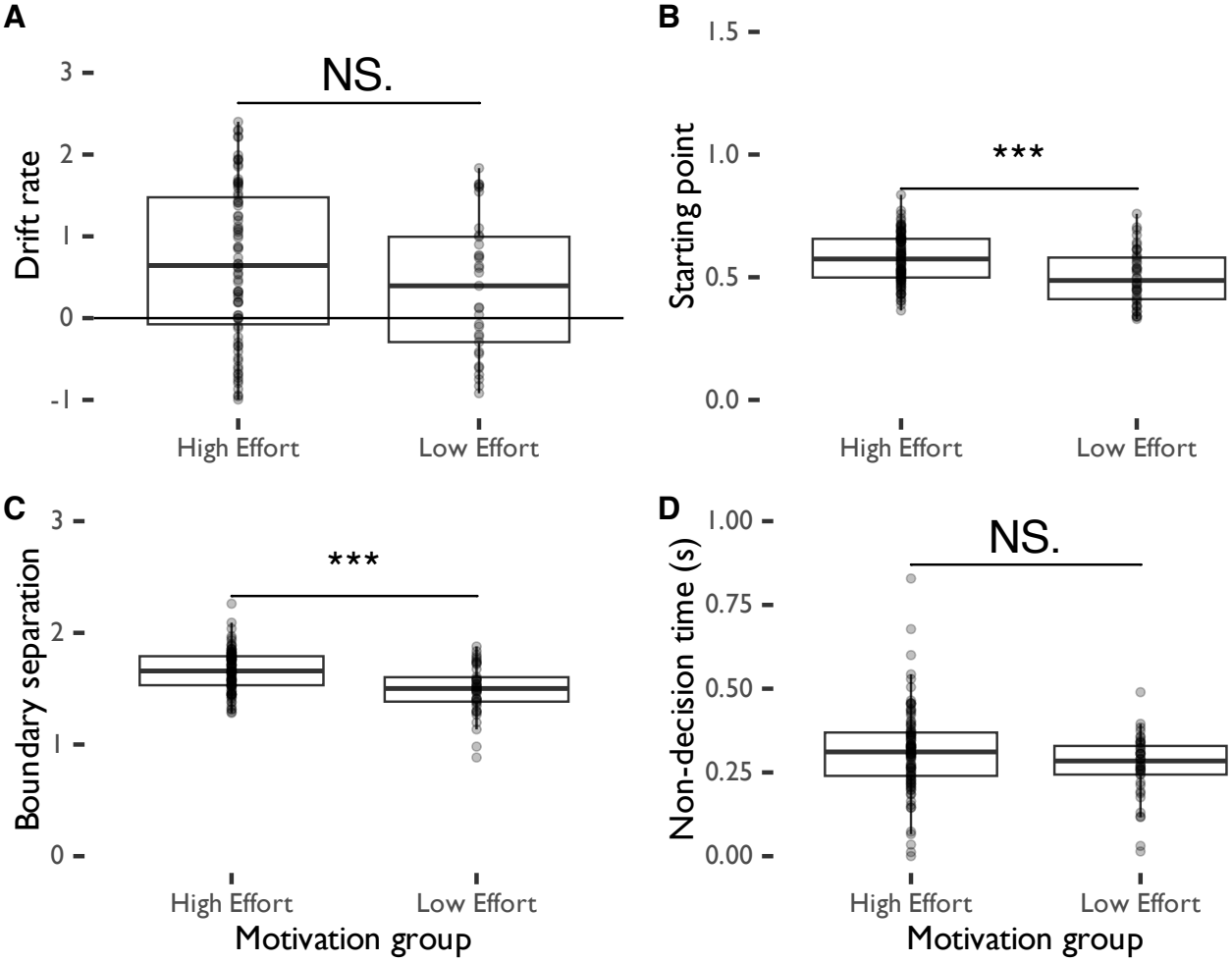

Figure 6

Outputs of a hierarchical Bayesian drift diffusion model fit to all participants in the effort choice task, divided by effort group. High effort participants had a significantly higher (B) starting point and (C) boundary separation compared to low-effort participants, but did not significantly differ on (A) drift rate or (D) non-decision time compared to low-effort participants.

Discussion

In this study, we investigated whether working memory performance, depressive traits, and chronic stress levels influence people's motivation and ability to consistently deploy cognitive effort for reward. Results showed that greater working memory ability significantly predicted the likelihood of systematically choosing high effort/high reward trials (whether the participant was classified in the high vs. low effort group), whereas

chronic stress, depression trait levels, and reward sensitivity were not predictive of effort deployment choices. Drift diffusion modeling further indicated that those who were categorized as high-effort participants required less evidence to select high effort/high reward trials, and were more strongly biased towards selecting these trials, than low-effort participants. Furthermore, working memory ability significantly predicted accuracy, while depressive traits predicted choice latency; both factors significantly differed depending on the effort required in the trial.

These results partially recapitulate findings from rodent research using the rCET regarding differences in performance and decision-making biases between those who select high effort trials more often, and those who select them less often. As in Cocker et al. (2012), participants who chose high effort trials over 70% of the time performed better than those who chose high effort trials 70% or less of the time, on LR - although not HR - trials. This finding could be explained by high effort group participants being less sensitive to rewards and punishments than low effort group participants, leading them to act sub-optimally and continue deploying effort even when they are not gaining more rewards from doing so.

Furthermore, our findings align with past work in rodents (Hales et al., 2024) in that our drift diffusion model results showed wider decision boundaries between HR and LR trials for high effort group compared to low effort group participants, as well as a starting point closer to HR trials for high effort group participants. Additionally, as with rodents, participants in the low effort group made faster choices than those in the high effort group on LR trials. However, participants in our study did not differ in drift rate between groups - while rodents in the equivalent high effort group had steeper drift rates on correct responses (Hales et al., 2024). Taken together, these findings could suggest similarities between humans and rodents in the influence of cognitive capabilities on performance when deploying more cognitive effort, as well as similarities in biases towards

deploying more effort or wanting higher rewards. Furthermore, they could indicate that impulsiveness to select a HR or LR trial could differ between humans and rodents. This could be explained by differences in the strength of reinforcement provided by the reward, which was a secondary reinforcement (points towards a monetary reward) in our task but a primary reinforcement (sugar pellets) in the rCET (Cocker et al., 2012; Hales et al., 2024), or by other differences between our task and the rCET as well as between humans and rodents in terms of how reward motivation is processed.

Additionally, previous studies with the rCET have shown no overall accuracy differences between high and low effort group participants across either LR or HR trials (Hosking et al., 2016; Silveira et al., 2020). However, in a recent, larger analysis, Hales et al. (2024) showed that rodents choosing more HR trials were slightly more accurate on HR trials, while rodents choosing more LR trials were slightly more accurate on LR trials. Although participants practiced task contingencies ahead of the main choice phase and the task difficulty was calibrated to working memory ability, individual differences in working memory - which predicted whether a participant selected high or low effort trials more often - still predicted these performance differences in humans. Furthermore, chronic stress - which can negatively impact availability of executive resources - did not explain accuracy or choice latency in this task. Thus, participants' willingness to deploy cognitive effort in our task was explained more by individual differences in executive function (working memory capability) (Sandra & Otto, 2018) rather than affective factors or the effects of affective factors on executive function (Slattery & Cryan, 2017). Note that although we did not measure executive control as a global construct in this study, visuospatial working memory ability is typically described as a process that falls withing the suite of executive functions (Miyake & Friedman, 2012).

Our findings suggest that choices to deploy cognitive effort for reward are primarily driven by participants' cognitive capacity (as measured by visuospatial working memory

ability) and not by depressive traits, chronic stress, or reward sensitivity, in participants within a non-clinical range of depression traits and chronic stress. Potentially, the aversiveness of expending cognitive effort for particpants with lower working memory capacity may have overridden overall sensitivity for reward. Additionally, although our population exhibited a wide range of depression scores - including those above clinical thresholds (Wang & Gorenstein, 2013) - this population was non-clinical. In contrast, much work on the impact of reward sensitivity on cognitive flexibility and related constructs has focused on participants who were clinically diagnosed with depression (Alloy, Olino, Freed, & Nusslock, 2016; Terpstra et al., 2023) or on rodents in which chronic stress was directly induced (Watt et al., 2017). In order to obtain the highest accuracy and reward possible, participants may have titrated the task's difficulty - through choosing a higher proportion of LR trials - to a level at which they can consistently complete the task and at which the value of their effort was greatest (Shenhav et al., 2013).

Choice latency indicates how long participants spend when deciding which effort level to choose. High effort group participants, who generally selected HR rewards more often and who were more biased towards selecting HR trials than low effort group participants, appear to have spent more time deliberating before selecting a LR trial than low effort group participants. They may have been trading off the benefits and costs of selecting a LR trial more consciously than low effort group participants were (Pruessner et al., 2020; Sandra & Otto, 2018), even as they performed significantly better than low effort group participants on LR but not HR trials. Indeed, our drift diffusion model results suggest that high effort group participants had to overcome a bias towards HR trials in order to select LR trials. This process could be driven by adjustments to effort deployment strategies based on performance, as suggested by recent interpretations of the Expected Value of Control theory (Shenhav, Prater Fahey, & Grahek, 2021). Through this framework, choosing a high proportion of high effort trials could be seen as optimizing effort deployment and making considered, model-based, decisions based on performance -

as reflected in increased choice latency among high effort group participants for LR trials - whereas selecting a high proportion of low effort trials could entail more model-free, rapid, and random decisions. Furthermore, participants with higher levels of depressive traits responded significantly faster across all trials, a result that runs counter to past work suggesting increased choice latency in reward tasks in rodents (Hales et al., 2023) or humans (Di Schiena, Luminet, Chang, & Philippot, 2013) with depressive-like traits. However, after Bonferroni correction, depressive traits and choice latency were not significantly correlated across all participants and trials ($t(702)$ = -1.21, $p = 1$, r = -0.05). As depressive traits did not impact accuracy, these findings could instead suggest a lack of engagement with decision-making in the task characterized by higher levels of automatic responding given high levels of depressive traits (Teachman, Joormann, Steinman, & Gotlib, 2012).

We found no significant sex differences in performance or choice latency in our study. Women generally present more with depression than men (Parker & Brotchie, 2010) and are also more impacted by chronic stress across the lifespan (Hodes & Epperson, 2019). However, the results of our study were primarily driven by visuospatial short-term memory ability, where sex differences are overall smaller and women may be better than men at memory for location (Voyer, Voyer, & Saint-Aubin, 2017) - a relevant measure in our task. Our undergraduate psychology student sample strongly skewed female; in future studies, it would be important to obtain a more balanced sample in order to further explore potential sex differences.

There are a number of caveats we must consider when interpreting these results. First, the study was conducted fully online on participants' own devices. While this allowed us to obtain a larger and better powered sample, differences in screen size and background distractions could have impacted participants' ability to encode the positions and colours shapes on each trial. These differences may have made the task more difficult

than originally intended for some participants. However, participant performance was still near ceiling on LR trials and very high on HR trials, so this was unlikely to have a large effect. Second, the set sizes used on the change detection task were modified from those originally used in Luck and Vogel (1997). The set size of 10 was removed from the pool of trials as pilot participants had very low performance at this set size. Although this change reduced the possible variety of trials used, participants still reported a maximum set size of 8 to be highly challenging. Third, the method used to calculate the K estimate slightly differed between the task - used to set the criterion level - and our analysis - used to establish the K estimate for each participant. In the task, the K estimate was calculated based on the current hit and false alarm rate after every trial, with the final K estimate being used to set the criterion for the choice phase of the task. In our analysis, we calculated the K estimate based on the full hit and false alarm rate at each set size. Because of rounding differences in these calculations, the K estimate values used in our analysis differ from those in our task by $M = 0.01$, $SD = 0.63$. We consider this difference to be small enough as to not have an effect on the difficulty of the task. Last, differences in performance that are explained by the K estimate could also be explained by the differences in set sizes available associated with being above or below the K criterion of 3 on set size = 4. However, the set sizes at each level of criterion were established with piloting such that the difficulty of each criterion level was matched as closely as possible.

Future studies could make further use of information about effort deployment choices that can only be captured in human studies. In particular, an expanding field of research uses qualitative approaches to investigate why participants make the judgments they do about effort deployment, as well as ask about participant experiences of task difficulty and the value of rewards vs. the effort required to obtain them (Vásquez-Rosati, Montefusco-Siegmund, López, & Cosmelli, 2019). Understanding the phenomenology of cognitive effort deployment choices would help us extend our understanding of how and why we make decisions to deploy more or less cognitive effort for reward, beyond

traditional self-report measures. This approach would also allow us to further explore how rodent-based constructs of cognitive effort deployment are reflected in human decision-making. Additionally, exploring how the brain represents information about effort task difficulty - especially in regions relevant to cognitive control like the dorsal anterior cingulate cortex (Shenhav et al., 2016; Yee et al., 2021) - through fMRI would help us better understand how motivational states in cognitive effort decision-making are reflected in neural circuitry.

Our study suggests that, as in rodents, significant individual differences exist in the human tendency to choose harder but more rewarding options in cognitive effort tasks. Using a visuospatial working memory task, we show that individual differences in accuracy and choice latency are primarily driven not by depressive traits or chronic stress - as has previously been shown in the rodent literature - but instead by working memory capability. These findings may help to inform clinical interventions aimed at increasing motivation to seek rewards and engage in work in everyday life, and illustrate the importance of translating and extending rodent work with human-specific measures.

Data and code availability

All task code, stimuli, data and code used to generate this manuscript and the figures are available at https://osf.io/c4h7s/.

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Legend

Figure 1. Layout of the experimental tasks. (A) The Monetary Incentive Delay Task, in which participants indicate their excitement in playing for tickets towards a monetary reward.(B) The calibration phase of the change detection task, where

participants saw an array of either 2, 4, 6, or 8 squares and indicated whether the final square that appeared (the probe) was of the same or a different colour from the square that appeared in the same location in the previously show array. (C) The reward phase of the change detection task, where participants saw an array of either 2 or 4, or 6 or 8, shapes on screen depending on their performance in the calibration phase of the task. Once again, participants indicated with a keyboard press whether the final square that appeared (the probe) is the same or a different colour from the square that appeared in the same location in the array. Here, if they made the correct decision, they would receive 1 point (low effort trial) or 10 points (high effort trial); they would receive 0 points for an incorrect decision.

Figure 2. Demographic distributions. Distribution of (A) depressive trait (BDI) proportion scores (score divided by total possible score), (B) perceived stress (PSS) scores, (C) anhedonia (DARS) scores, and (D) mean reward anticipation scores by sex. BDI = Beck Depression Inventory, PSS = Perceived Stress Scale, DARS = Dimensional Anhedonia Rating Scale.

Figure 3. Plot of binomial logistic regression predicting whether participants were in the high effort vs. low effort group. Binomial logistic regression predicting whether participants were in the high effort vs. low effort group. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected.

Figure 4. Accuracy and choice latency by motivation group. Accuracy and choice latency in the choice phase of the change detection task by motivation group (high effort vs. low effort group). The choice latency plot has been log-transformed on the y-axis to more clearly show small choice latency values. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected.

Figure 5. Accuracy and choice latency by working memory ability. (A) Accuracy and (B) choice latency in the reward phase of the change detection task by working

memory ability (K estimate). The choice latency plot has been log-transformed on the y-axis to more clearly show small choice latency values.

Figure 6. Drift diffusion model outputs for high and low effort participants. Outputs of a hierarchical Bayesian drift diffusion model fit to all participants in the effort choice task, divided by effort group. High effort participants had a significantly higher (B) starting point and (C) boundary separation compared to low-effort participants, but did not significantly differ on (A) drift rate or (D) non-decision time compared to low-effort participants.

Table 1. Demographic information for all participants, by sex and effort deployment group. BDI_{prop} = Beck Depression Inventory II proportion score (score divided by max score). PSS = Perceived Stress Scale score. DARS = Dimensional Anhedonia Rating Scale. Ant. = mean reward anticipation in the behavioural monetary incentive delay task. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected.

Table 2. Binomial logistic regression predicting whether participants were in the high effort vs. low effort group. High effort group: > 70% HR trials selected; low effort group: <= 70% HR trials selected. BDI (prop. score) = depression score on the Beck Depression Inventory, PSS = Perceived Stress Scale. Proportion scores are scores divided by total possible score. AIC = Akaike information criterion, BIC = Bayesian information criterion, ICC = intraclass correlation, RMSE = root mean squared error.

Table 3. Multi-level model analysis coefficients and standard errors for accuracy in the reward phase of the task. BDI (prop. score) = depression score on the Beck Depression Inventory, PSS = Perceived Stress Scale. Proportion scores are scores divided by total possible score. AIC = Akaike information criterion, BIC = Bayesian information criterion, ICC = intraclass correlation, RMSE = root mean squared error.

Table 4. Multi-level model analysis coefficients and standard errors for choice

latency in the reward phase of the task. BDI (prop. score) = depression score on the Beck Depression Inventory, PSS = Perceived Stress Scale. Proportion scores are scores divided by total possible score. AIC = Akaike information criterion, BIC = Bayesian information criterion, ICC = intraclass correlation, RMSE = root mean squared error.

Table 3

Multi-level model analysis coefficients and standard errors for accuracy in the reward phase of the task. BDI (prop. score) = depression score on the Beck Depression Inventory, PSS = Perceived Stress Scale. Proportion scores are scores divided by total possible score. AIC = Akaike information criterion, BIC = Bayesian information criterion, ICC = intraclass correlation, RMSE = root mean squared error.

	Multi-level model: Accuracy
(Intercept)	0.64***
	(0.02)
Sex	0.01
	(0.01)
Working memory ability (K estimate)	0.01**
	(0.00)
BDI (prop. score)	−0.01
	(0.04)
PSS	0.00
	(0.00)
Reward anticipation	0.00
	(0.00)
Effort level	0.25***
	(0.01)
SD (Intercept participant)	0.04
SD (Observations)	0.10
Num.Obs.	542
R2 Marg.	0.592
R2 Cond.	0.656
AIC	−840.0
BIC	−801.3
ICC	0.2
RMSE	0.09

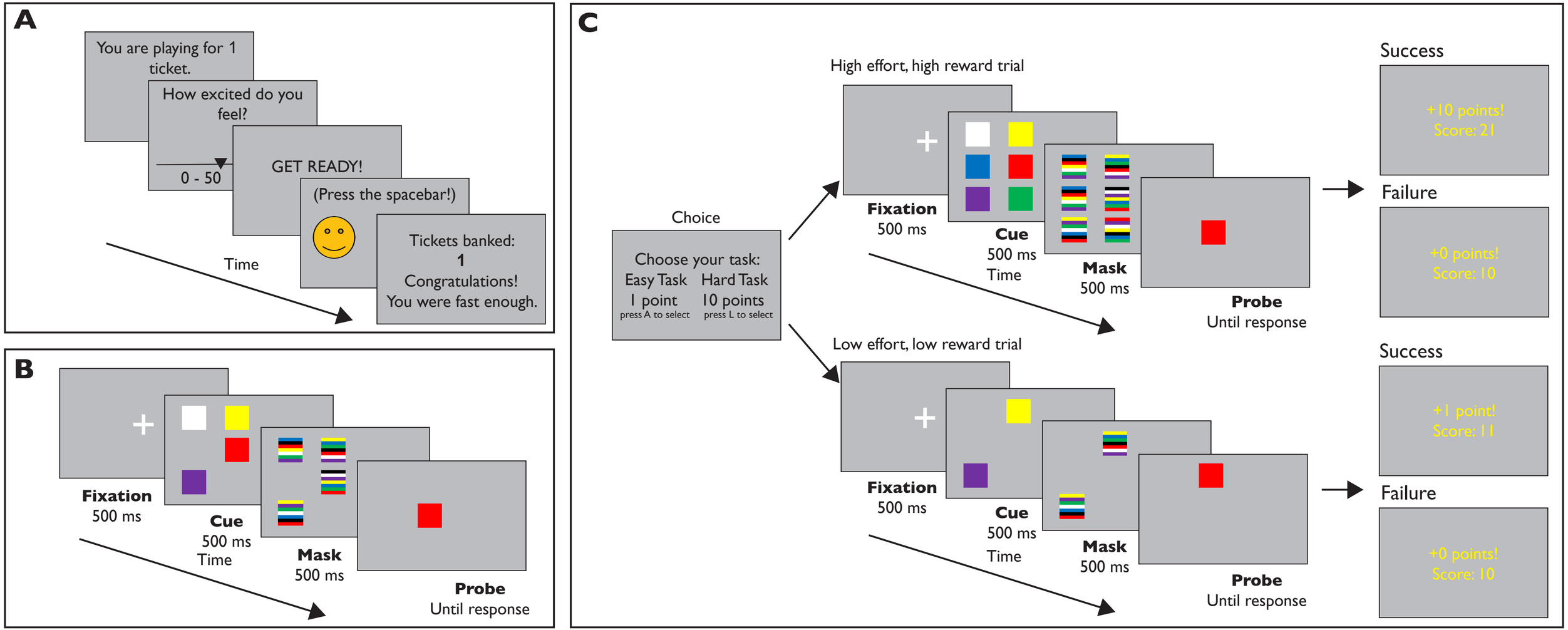
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

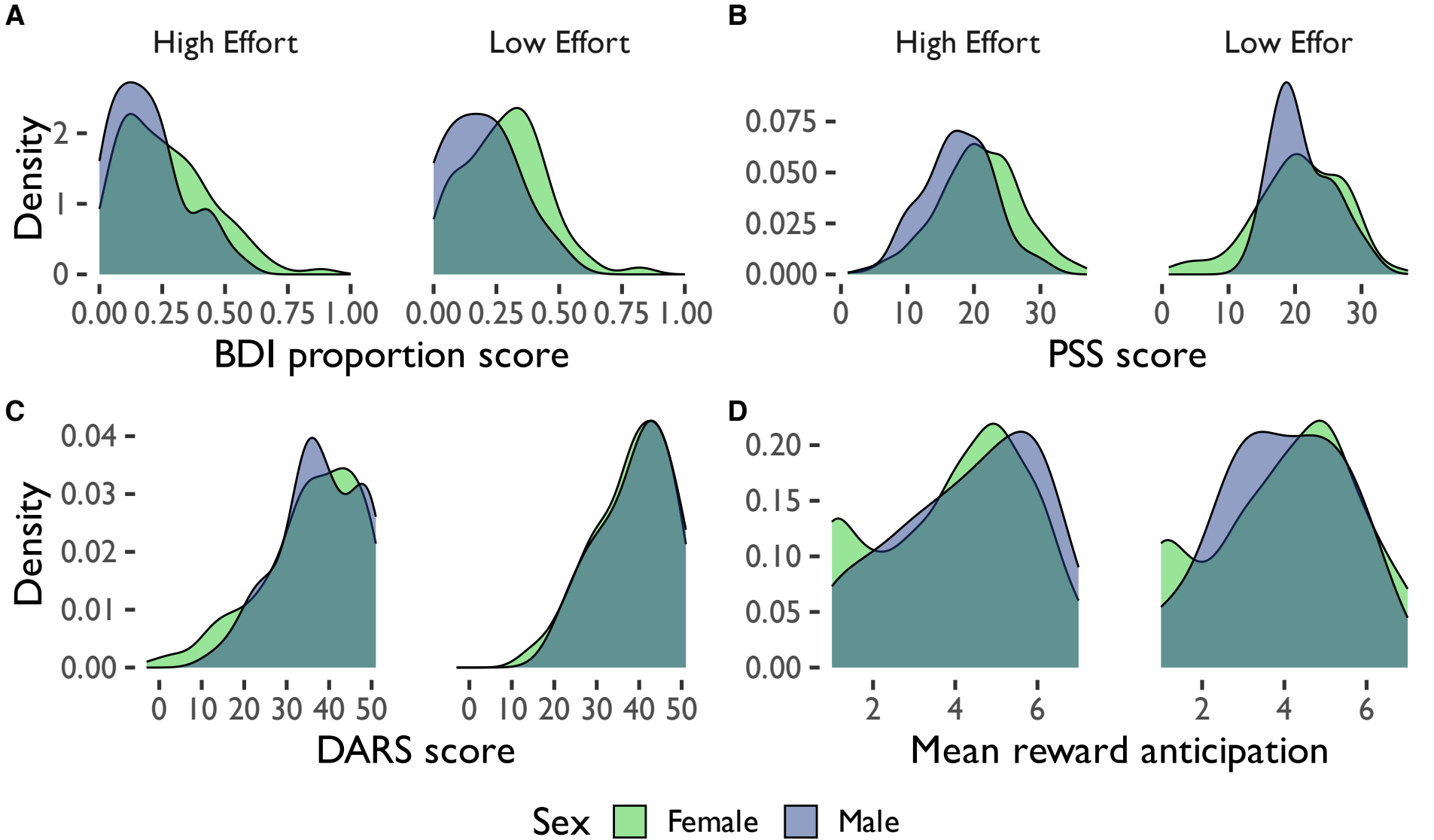
Table 4

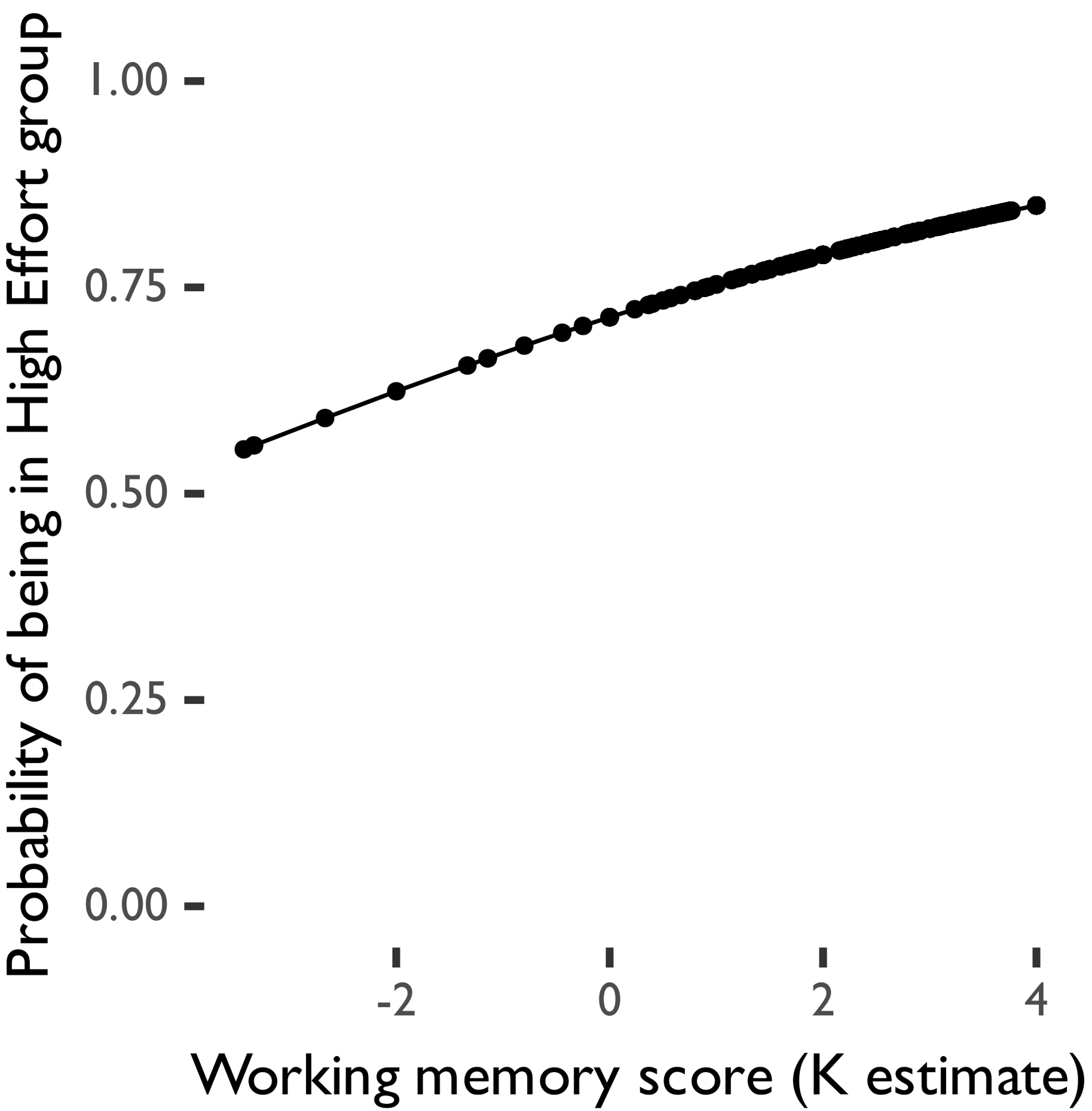
Multi-level model analysis coefficients and standard errors for choice latency in the reward phase of the task. BDI (prop. score) = depression score on the Beck Depression Inventory, PSS = Perceived Stress Scale. Proportion scores are scores divided by total possible score. AIC = Akaike information criterion, BIC = Bayesian information criterion, ICC = intraclass correlation, RMSE = root mean squared error.

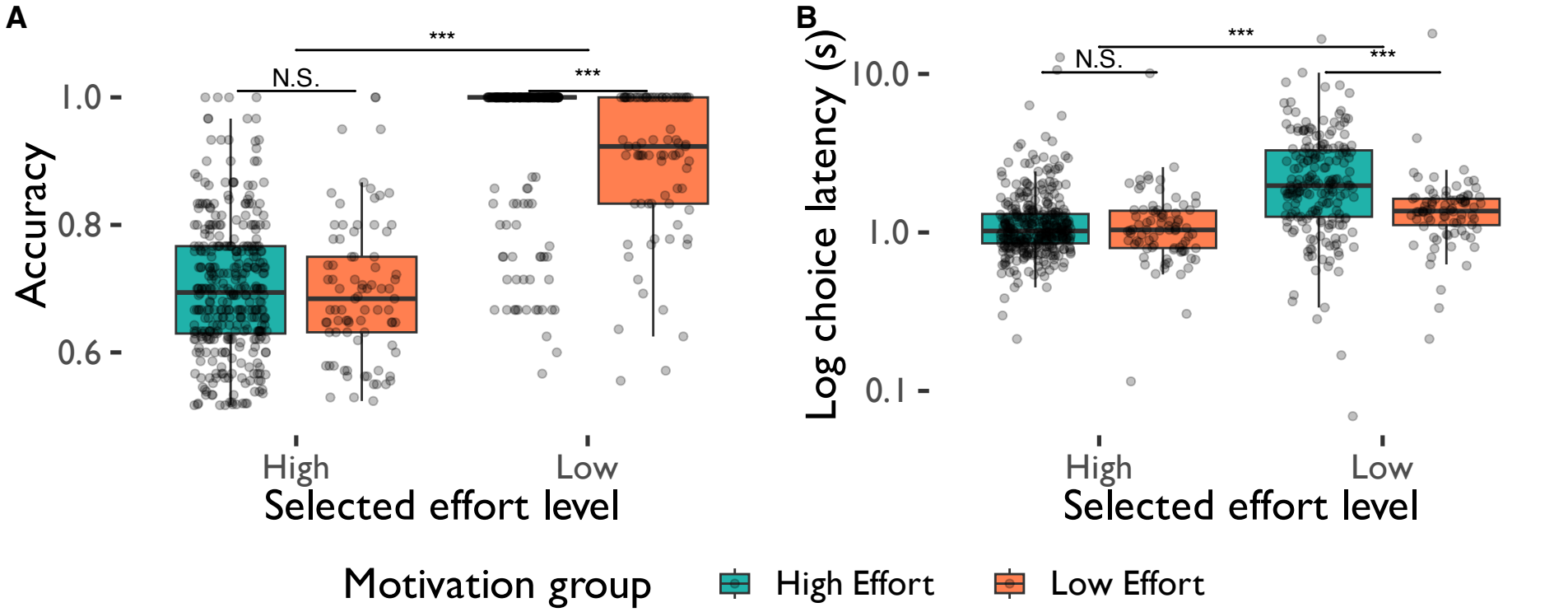
	Multi-level model: Choice latency
(Intercept)	1.25***
	(0.34)
Sex	−0.07
	(0.17)
Working memory ability (K estimate)	0.05
	(0.05)
BDI (prop. score)	−1.11*
	(0.54)
PSS	0.01
	(0.01)
Reward anticipation	−0.04
	(0.04)
Effort level	1.06***
	(0.13)
SD (Intercept participant)	0.18
SD (Observations)	1.53
Num.Obs.	542
R2 Marg.	0.114
R2 Cond.	0.127
AIC	2042.9
BIC	2081.6
ICC	0.0
RMSE	1.51

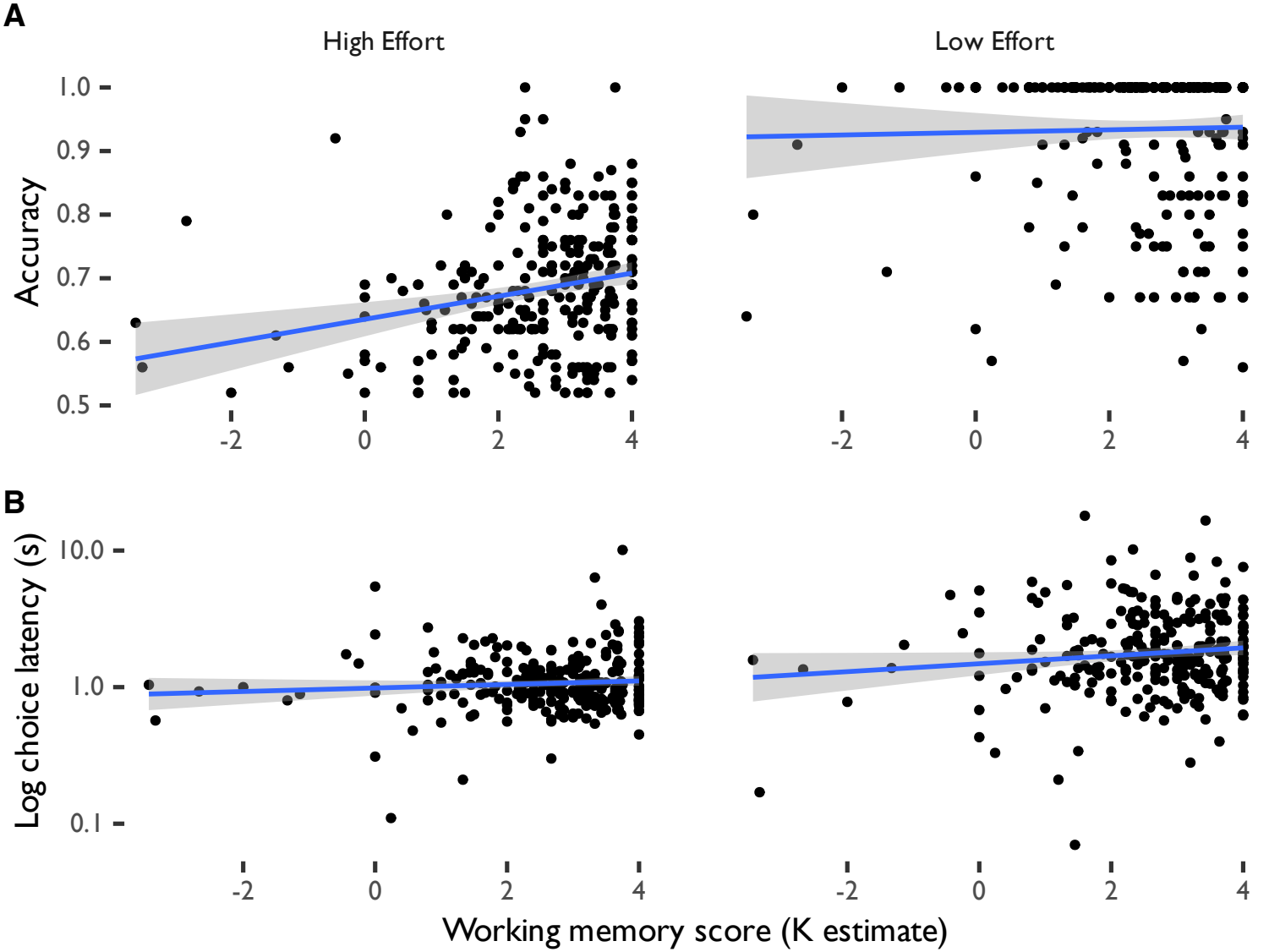
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

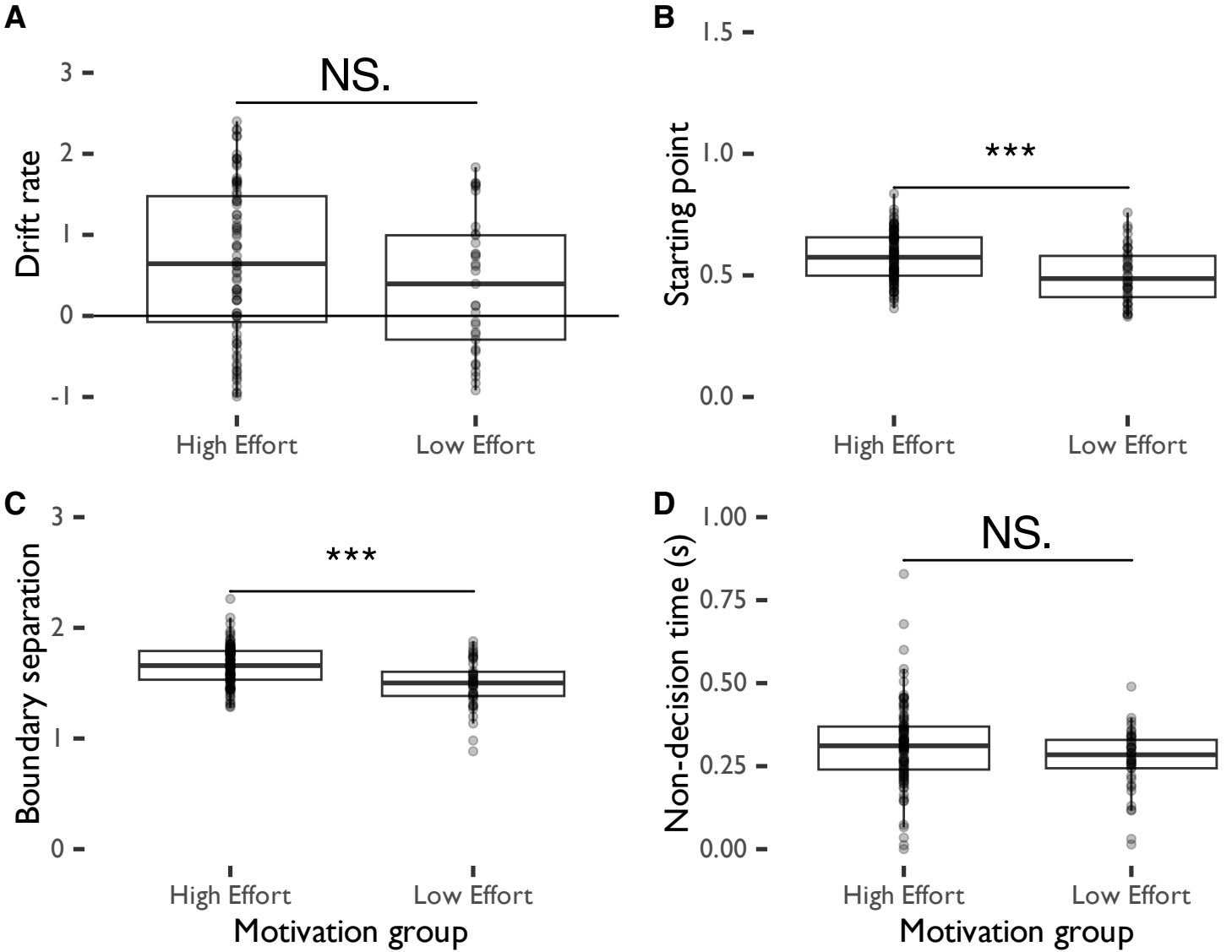

A
You are playing for 1 ticket.
How excited do you feel?
0 - 50
GET READY!
(Press the spacebar!)
Tickets banked:
1
Congratulations!
You were fast enough.
Time
B
Fixation
500 ms
Cue
500 ms
Mask
500 ms
Probe
Until response
Time
C
Choice
Choose your task:
Easy Task
1 point
press A to select
Hard Task
10 points
press L to select
High effort, high reward trial
Fixation
500 ms
Cue
500 ms
Mask
500 ms
Probe
Until response
Time
Success
+10 points!
Score: 21
Failure
+0 points!
Score: 10
Low effort, low reward trial
Fixation
500 ms
Cue
500 ms
Mask
500 ms
Probe
Until response
Time
Success
+1 point!
Score: 11
Failure
+0 points!
Score: 10


A
High Effort
Low Effort
Density
2
1
0
0.00 0.25 0.50 0.75 1.00
0.00 0.25 0.50 0.75 1.00
BDI proportion score
B
High Effort
Low Effor
0.075
0.050
0.025
0.000
0 10 20 30
0 10 20 30
PSS score
C
0.04
0.03
0.02
0.01
0.00
Density
0 10 20 30 40 50
0 10 20 30 40 50
DARS score
D
0.20
0.15
0.10
0.05
0.00
2 4 6
2 4 6
Mean reward anticipation
Sex
Female
Male


Probability of being in High Effort group
1.00
0.75
0.50
0.25
0.00
-2
0
2
4
Working memory score (K estimate)


A
***
N.S.
***
1.0
0.8
0.6
Accuracy
High
Low
Selected effort level
B
***
N.S.
***
10.0
1.0
0.1
Log choice latency (s)
High
Low
Selected effort level
Motivation group
High Effort
Low Effort


A
High Effort
Low Effort
Accuracy
1.0
0.9
0.8
0.7
0.6
0.5
-2
0
2
4
B
Log choice latency (s)
10.0
1.0
0.1
Working memory score (K estimate)


A
NS.
Drift rate
3
2
1
0
-1
High Effort
Low Effort
B
***
Starting point
1.5
1.0
0.5
0.0
High Effort
Low Effort
C
***
Boundary separation
3
2
1
0
High Effort
Low Effort
Motivation group
D
NS.
Non-decision time (s)
1.00
0.75
0.50
0.25
0.00
High Effort
Low Effort
Motivation group