Do cognitive and physical effort costs affect choice behavior similarly?

Li Xin Lim[1*], Madison Fansher[2], Sébastien Hélie[1]

[1]Department of Psychological Sciences, Purdue University, 703 3rd St., West Lafayette, IN 47907, USA;

[2]Department of Psychology, University of Michigan, 530 Church St., Ann Arbor, MI 48109, USA.

* lim226@purdue.edu

Abstract

Performing an action often incurs a cost, such as exerting effort for a reward. Previous studies used the Effort Expenditure for Reward Task (EEfRT) to show devaluation of reward with physical effort. However, it is unclear if a similarly structured attentional task would produce a similar devaluation with cognitive effort. In the present work, we propose a new task called the "shell game task" (SGT) as a cognitive effort-based decision-making paradigm. Participants performed both the EEfRT and SGT in a within-subject design. Using computational models of choice behavior, we showed that effort cost induced by the variability of task demands in the SGT is similar to the effort cost from the existing EEfRT in the devaluation of a given outcome in action choice selection. This result suggests that effort cost may be a stable idiosyncratic trait across the two tasks and shows how computational approaches can be used to estimate and compare measures of effort. In addition, the results suggest that the SGT can be used as an alternative to the EEfRT with subject populations with motor deficits.

Keyword

Effort discounting, cognitive effort, physical effort, decision-making

1. Introduction

In everyday life, people encounter different situations where decisions regarding the course of actions to obtain a reward need to be made. These decisions often incur a cost, such as patience or effort to obtain a reward. Sayings like "no pain no gain" are common, and as a result, people often deliberate if a reward is worth working for. Such decisions can be simple, like debating if one should make the physical effort to walk to the refrigerator to get a favorite snack. In more difficult cases, the process of achieving a goal may be tiring, for instance, working out daily to get your body toned. It is easy to give up when a great amount of effort is required. Moreover, it is hard to even initiate actions when anticipating the work needed over time.

When facing effortful actions, one often estimates the costs and benefits of available options and selects the most beneficial response in a given circumstance (Rangel, Camerer, & Montague, 2008). In decision-making, effort is regularly regarded as a principle cost, whereby effort discounting devalues rewards by decreasing the utility of related outcomes (Botvinick et al., 2009; Kool et al., 2010; Kurniawan et al., 2010). Thus, when available options include choices with high effort costs, the choice can become less appealing (Iyengar & Lepper, 2000; Kool et al., 2010).

Apart from physical effort, the willingness to engage in cognitively demanding tasks can also be characterized by effort cost. The concept of cognitive effort is intuitive as it is accompanied by a phenomenological experience in that engaging in a cognitively demanding task "feels" different compared to daydreaming. The study of cognitive effort is important because of its impact in various scenarios, from arithmetic, problem solving, and rational reasoning (Shah &

Oppenheimer, 2008; Toplak et al., 2011), to economic decision-making (Garbarino & Edell, 1997; Payne et al., 1988; Shah & Oppenheimer, 2008; Smith & Walker, 1993; Westbrook & Braver, 2015), and much more. Cognitive effort expenditure may also act as a predictor of academic achievements (Arafa et al., 2018; von Stumm et al., 2011) as it can be defined as the amount of cognitive capacity allocated to learning and task performance (Arafa et al., 2018; De Jong, 2010). The willingness to expand cognitive effort in discounting motivation is a goal-directed behavior with its influence in managing cognitive control to reach a valuable goal (Shenhav et al., 2013). Moreover, Kool et al. (2010) showed the relevance of the law of less work or the tendency to minimize cognitive effort exertion in order to conserve limited cognitive resources. The study showed participant's avoidance of cognitive demand in behavioral experiments where participants chose freely between courses of action that involved various demand levels of controlled information processing. Participants' bias to select the less demanding choice changes according to the task incentives but were not completely accounted for by the strategic avoidance of errors, minimization of time on task, or maximization of rate of goal achievement.

Effort-based decision-making paradigms are typically carried out to determine how physical or cognitive effort affects the value of a given outcome in action choice selection (Treadway & Zald, 2011). The Effort Expenditure for Reward Task (EEfRT) has often been used in previous studies to examine effort-based decision-making (Treadway et al., 2009). The EEfRT has been used widely to study choice selections that involve varying degrees of physical effort allocation for a monetary reward (Gill et al., 2020; Treadway et al., 2009). The EEfRT can be presented as a key pressing game, where participants decide on the level of physical effort that they are willing to engage in to achieve varying monetary rewards. The reward magnitudes are usually presented with differing probability levels for reward receipt. This combination allows for examining how reward magnitude, probability of reward receipt, and expected value modulate effort-based decision-making. Studies using the EEfRT show evidence for the avoidance of high effort tasks with fixed magnitudes of reward (Kool et al., 2010). In addition, people with schizophrenia and major depression often show decreasing tendencies to select high effort options to maximize reward in the EEfRT (Barch et al., 2014; Hammar, 2009; Hartlage et al., 1993). Effort aversion is often seen in motivational disorders and particularly in neurobiological illnesses with dopaminergic dysfunction (Chong & Husain, 2016; Salamone & Correa, 2018), where effort deficiency leads to poor performance on cognitively demanding tasks without affecting performance in tasks with lower cognitive demands (Cohen et al., 2001; Hammar, 2009; Hartlage et al., 1993; Zakzanis et al., 1998).

Many studies have been carried out to identify the relationship between cognitive and physical effort. Białaszek et al. (2017) showed both physical and cognitive effort devalues rewards less in lower effort tasks and more in higher effort tasks. Moreover, the ventral striatum has been suggested by Schmidt et al. (2012) to be a common motivational node in representing the expected reward after effort exertion driving both the cognitive and the physical domains. However, not all studies have shown equivalent scaling of cognitive and physical effort. While physical effort measured through the EEfRT has been used to compare willingness to expend effort for rewards in patients with major depressive disorders and healthy controls (Treadway et al., 2012), adapted cognitive effort tasks relying on working memory have failed to discriminate patients with major depressive disorders from control groups (Tran et al., 2021). In a study comparing the EEfRT to a cognitive set-switching task, participants tend to choose the hard task more often in the cognitive task as compared to the EEfRT, even though they perceived the cognitive counterpart to be more difficult (Lopez-Gamundi and Wardle, 2018).

The issue with most of the available studies comparing decisions about physical and cognitive effort for reward is the failure in direct comparison between the physical and cognitive measures. Studies on physical effort typically measure either single sustained or multiple accumulated muscle contractions. However, such measures of physical effort is often contrasted with cognitive paradigms such as numerical Stroop tasks (Schmidt *et al.*, 2012), memory search tasks (Ennis et al., 2013), working memory N-back tasks (Westbrook et al., 2013), set-switching tasks (Lopez-Gamundi and Wardle, 2018), and more. These tasks measure avoidance of cognitive effort as a free-choice, often measuring the ability to suppress and switch. In contrast, most physical effort measures are either repeated or single sustained muscle contractions. As an analogy, think about the difference between lifting a heavy weight one time (similar to task switching) vs. repeatedly lifting a lighter weight (similar to repeatedly pressing a key). Both tasks are effortful, but they are very different. As a result, the lack of translational and parallel measures of physical and cognitive effort costs in previous studies may prevent appropriate comparison of effort discounting between the two domains. A better alternative for tasks examining cognitive effort discounting may be related to attention maintenance, where the effort intensity is a measure of maximum voluntary effort sustained over a set temporal duration. Attention maintenance over a shorter period requires less sustained effort as compared to the same task over a longer duration, similar to the physical counterpart in EEfRT, whereby the smaller number of rapid key presses requires less sustained effort than the case when more rapid key presses are required.

1.1 The proposed cognitive task

In this article, we propose using a new task called the “shell game task” (SGT) as an alternative to the EEfRT. The task requires target trailing by following the movement and position of a target. The effort required in the SGT can be adjusted by changing the speed of movement, duration of movement, and the number of objects in motion. Similar to the key-pressing task in the EEfRT, participants can select a hard or easy choice as a function of the reward presented. The choice selection reflects the cognitive effort expenditure as a measure of the voluntary mobilization of cognitive resources. In the EEfRT, since the task demands varies by changing the intensity and duration of sustained effort in the form of the physical work done, the comparison of the choice offered is rather straightforward. Similarly, the task demands in the SGT varies in terms of the intensity and duration of sustained attention. Thus, the SGT may be more translational to the EEfRT.

1.2 Aim of the study

The main goal of this experiment was to construct a cognitive effort-based reward-motivated decision-making task that could be appropriately compared to performance in the EEfRT. After creating the task (SGT), our next goal was to demonstrate that willingness to exert effort in the SGT would parallel willingness to exert physical effort in the EEfRT. To achieve this goal, we first demonstrated the presence of effort discounting in the cognitive paradigm. The effort comparison in the same domain is driven by the two levels of task demands. The difference in task demands in the same domain differed in terms of the “force” exerted over time. With consistent task demand difference throughout the paradigm, we hypothesized that participants would choose to exert more effort in both cognitive and physical paradigms when reward motivation was sufficiently high. With this, we hypothesized similar motivation discounting with effort when the willingness to exert effort was matched in the two domains. The present study focused solely on the impact of task demand differences on reward motivation, leaving out the assessment of the nature of cognitive and physical demands. In line with the idea that motivating effects of rewards can be offset by task demands or reduce the net utility of effort exertion (Apps et al., 2015; Kool et al., 2010; Shenhav et al., 2013), effort cost was computed as the turning point to choose the relatively demanding task as reward motivation increased. People choose to work less when the reward motivation was less than the effort cost, and choose to work more if the work was accompanied with reward motivation that is greater than the effort cost. Thus, the study compared the willingness to exert effort to obtain a certain reward in the physical and cognitive paradigms. If increasing task demands reduces the motivation to obtain a higher reward in both the proposed SGT and the existing EEfRT, the SGT may be deemed an appropriate alternative to the EEfRT.

Another goal of this research was to explore if the pattern of effort discounting in the two domains would hold when varying the reward-uncertainty combinations as seen in the original EEfRT. This was to show task stability with different incentive combinations. As a result, the possible changes to effort discounting in cognitive or physical paradigms were investigated according to the changes in reward-uncertainty combinations in different risk-reward conditions. However, it is also noted that subjective probabilities might not scale linearly; the subjective difference in the probability combinations in one risk condition might not be perceived as the same as in the other risk conditions, despite the same objective difference between two probabilities (Winman et al., 2014). Hence, we speculate a low possibility of changes in choice behavior with the adjusted probabilities in the risk conditions given the tendency to underestimate or overestimate probabilities or risk in the environment. The study aims can be achieved by (1) demonstrating that participants discount motivation with a similar estimated effort cost across the two tasks, (2) examining if the two measures are similarly sensitive to changes in reward motivation, and (3) testing task stability with different risk-incentive combinations. Moreover, through the comparison of the SGT and the EEfRT, this work compared the willingness to exert effort for reward in the cognitive and physical domains.

2. Methods

To demonstrate that participants discount motivation with similar effort cost across the two tasks and that the two measures are similarly sensitive to changes in reward motivation, we used the EEfRT and the new SGT to measure willingness to exert effort with varying rewards. The effort cost in the two tasks was compared using computational modelling.

2.1 Participants

One hundred twenty-three participants were recruited from the Purdue University undergraduate population. Up to 10 participants were recruited for each session of the experiment, and the participants were run simultaneously on individual workstations separated by walls. Each participant was given credit for participation as partial fulfillment of a course requirement. Participants gave written informed consent and all procedures were approved by the Purdue University Human Research Protection Program Institutional Review Board. The participants took part in the study voluntarily and anonymously. The study was carried out in accordance with the Declaration of Helsinki.

2.2 Materials and Procedure

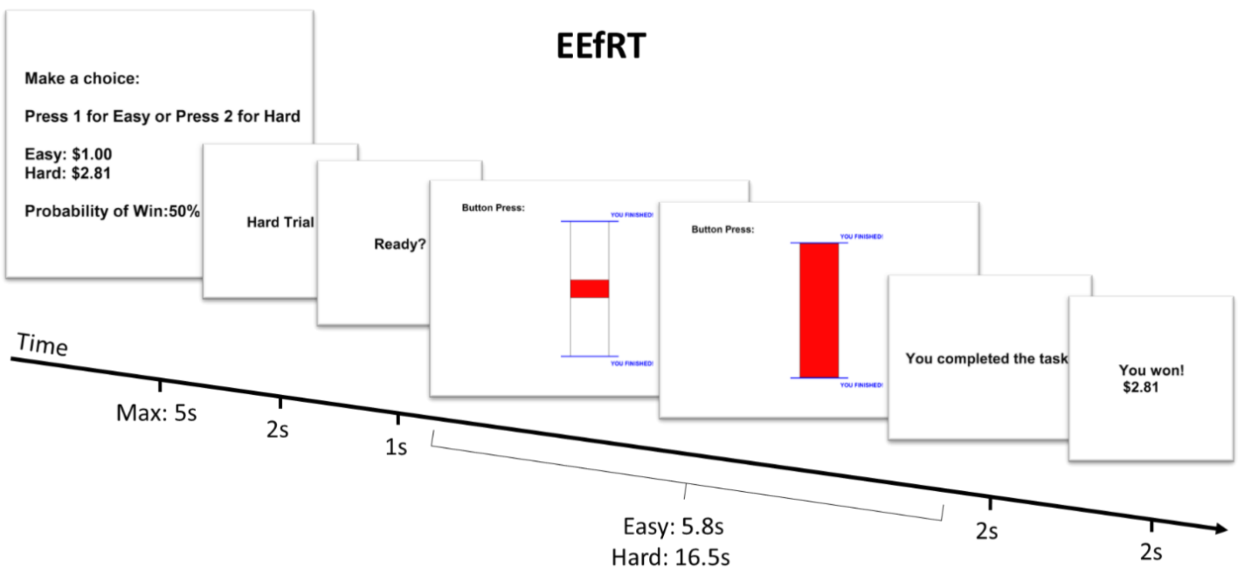
Each participant performed both the EEfRT and the SGT in random order of EEfRT-SGT (n = 64) and SGT-EEfRT (n = 59). The tasks were displayed in a 21-inch monitor with 1,920 ×1,080 resolution. The experiment was controlled by in-house programs written using PsychoPy (Peirce et al., 2019).

2.3 Effort Expenditure for Reward Task (EEfRT)

Participants were presented with a white rectangular bar in the middle of the screen, with a red starting block in the center and two finishing lines on the ends of the rectangle bar. Upon pressing the key ‘b’ on the keyboard, the red block expanded and gradually filled the area of the white bar. The red block expanded after each key press, so that constantly holding the keys would not expand the red block. The participants were instructed to repeatedly press the key 'b' on the keyboard until the red block reached the finish lines. The sequence and timing of the EEfRT is shown in Figure 1.

Figure 1

Task flow of the EEfRT.



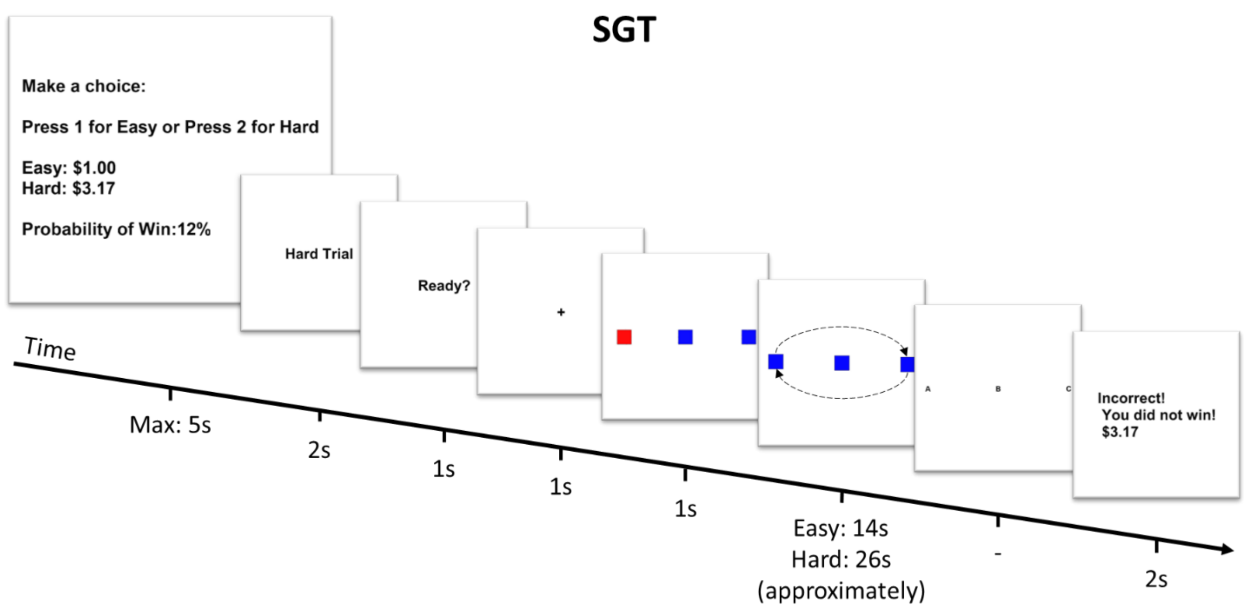
Note. The reward and win-probability were shown at the start of each trial. After a decision was made, the participants were required to perform the key-pressing task within a time limit. Feedback on the completion of the task and reward won were then displayed.

2.4 <u>Shell Game Task</u>

Participants were presented with three blue squares in the middle of the screen equally spaced from each other. One of the blue squares, the target, turned red for 1 second and back to blue. The three squares were then "shuffled" on the screen, in which the squares would randomly move around on the screen (two at a time) to the three possible target locations multiple times within the shuffling period. Participants were required to track the target square as it was shuffled with the other two distractor squares. Once the shuffling had stopped, the participant was asked to choose the final placement of the target square by pressing one of the keys on the keyboard labelled “A”, “B”, or “C”. Key “s” on the keyboard was labeled as “A”, key “g” as “B”, and key “k” as “C”. The sequence and timing of the SGT is shown in Figure 2.

Figure 2

Task flow of the SGT.



Note. The reward and win-probability were shown at the start of each trial. After a decision was made, the participants were required to perform the SGT and feedback on the accuracy and reward won was displayed.

2.5 <u>Common choice structure to both tasks</u>

Participants underwent 48 trials in both EEfRT and SGT. At the beginning of each trial, participants were asked to choose to perform either the hard or easy version of the current task (SGT or EEfRT). In the EEfRT, the rate of key presses required was greater in the hard version

(100 key presses in 16.5s) as compared to the easy version (30 key presses in 5.8s). In the SGT, the hard choices (70 shuffles with displacement of 4 pixels per screen refresh, with 60Hz refresh rate) had more shuffles with higher shuffling speed as compared to the easy version (30 shuffles with displacement of 3 pixels per screen refresh, with 60Hz refresh rate). The difficulty specifications in the tasks were made such that success in the hard version of the tasks was achieved in about 85% of the trials, while the easy version yielded success in approximately 95% of the trials in pilot experiments. Participants had to make a selection within five seconds, else the difficulty level was randomly selected.

The participants were informed that they would receive monetary rewards according to their performance during the experiment and that the rewards would be given at the end of the experiment when every participant in the same session was done with both tasks. Rewards for the hard choices of the tasks were greater than easy choices. The reward for the hard version of the tasks varied from trial-to-trial and ranged from $1.25 to $5.35, while the reward for the easy version of the tasks was always $1. The participants were told that they had to accurately complete the particular trial to get the reward, but that the reward would not necessarily be granted even though they succeeded during the trial. The probability of winning the reward was shown to the participants along with the reward at the beginning of each trial when they were given the choice to select between the hard and easy versions of the task. The probability of winning the reward was the same for both easy and hard rewards for each trial if the task was completed successfully. The participants were informed if they had received the reward at the end of each trial. At the end of both experiments, two rewards they won from each task were selected randomly, and the sum was given to the participants as a monetary compensation.

2.6 Discounting stability across tasks with different risk-incentive combinations

To achieve our aim in showing task stability with different risk-incentive combinations, changes in effort cost in both the motor and cognitive tasks with three risk-incentive conditions were examined. The three risk conditions were low (n = 40), medium (n = 43), and high (n = 40). The combinations of reward amount and uncertainty of winning the reward were adjusted to match the risk-incentives conditions, as shown in Table 1. It should be noted that each participant only performed the experiment under one of the risk conditions, which was randomly assigned to them.

The probability of winning reward and reward structures in the medium risk conditions followed that from the original EEfRT (Treadway et al., 2009). The low and high risk conditions were designed such that the reward probabilities in each condition differed by 0.12 from the medium risk condition such that there is a constant difference between the corresponding probabilities in all risk conditions and the probabilities are still within the range from 0 to 1. For example, the lowest win-probability (i.e., 0.24) in the low risk condition was 0.12 higher than that in the medium risk condition (i.e., 0.12). In the high risk condition, the lowest win-probability (i.e., 0.00) was 0.12 lower than that in the medium risk. With the subtraction of 0.12 from the lowest win-probability in the medium risk group, the lowest win-probability in the high risk condition was 0, wherein no reward was given to the participants regardless of the choice or the performance in trials where the win-probability was 0. With the addition of 0.12 to the greatest win-probability in the medium risk group, the greatest win-probability in the low risk condition was 1, wherein participants were guaranteed the reward if they managed to perform the task in trials where the win-probability was 1. The goal of this manipulation was to explore possible changes in choice selection in both tasks, especially in trials where participants were guaranteed reward with good performance or if no reward was given regardless of performance.

Note that the expected reward was kept constant for all risk conditions, which meant pairing higher risk conditions with higher mean rewards. This approach was used to balance the change in win-probability with the reward, so that the participants did not get overly motivated in the low risk condition or under-motivated in the higher risk condition.

Table 1

Reward and win-probability combinations for the three conditions

Conditions (risk group)	Low	Medium	High
Win-probability	0.24, 0.62, 1.00	0.12, 0.50, 0.88	0.00, 0.38, 0.76
Mean reward ($)	2.40	2.98	3.92

2.7 Modelling choices

To determine if the effort cost and decision mechanism was common across the two tasks, computational models of choice behavior were fitted to participants' responses to estimate the subjective utility of each offer to individual participants. The subjective utility estimate was a linear model that predicted a constant discounting of the expected value of reward as effort increased.

The subjective utility of a hard choice was modelled as:

$$U_h(t) = R_h(t)p(t) - E \tag{1}$$

where $R_h(t)$ is the reward offered in trial *t* for the hard choice, $p(t)$ is the win-probability in trial *t* if the participant is successful, and E is the relative effort cost of the hard choice as compared to the baseline option (easy choice). The product of $R_h(t)$ and $p(t)$ gives the expected value of the hard choice in trial *t*, which represents the value of reward, given the probabilities of winning it after a successful trial. E is a free parameter representing the relative effort cost of performing the hard version of the task in comparison to the easy version of the task. When selecting the easy choice, the amount of reward was always $1, hence, $R_e(t)$ was set to 1 for the easy selection. With E as the relative effort cost to the baseline option (the easy choice), E was set to 0 for the computation of the subjective utility of easy choice, so $U_e = p(t)$.

We fitted the subjective utility functions to the choices participants made in each task. The subjective utility of each choice offer for each participant was referenced to the subjective utility of the baseline offer. The model decision was implemented using a softmax function:

$$Pr_h(t) = \frac{e^{\alpha U_h(t)}}{e^{\alpha U_e(t)} + e^{\alpha U_h(t)}} \tag{2}$$

where $Pr_h(t)$ represents the probability of choosing the hard choice that has a subjective utility of $U_h(t)$ in trial *t*, while the easy choice had utility $U_e(t)$; α is the inverse temperature of the softmax function, which represents the stochasticity of decisions, i.e., the sensitivity to the subjective utility in a given trial. Maximum stochasticity is obtained when α is set to zero, while the randomness decreases when α increases, indicating a strategy to choose the higher value offer. The probability of selecting the easy choice in trial *t*, $Pr_e(t)$, was simply $1 - Pr_h(t)$.

We compared the stability of the effort cost of each participant in the two tasks by estimating the relative effort cost (E) and the inverse temperature (α). E and α were estimated with five models using the same softmax function. The differences in the models are whether E or α were modelled separately for the two tasks or represent a common mechanism (2^2 + 1 null model = 5 models). Table 2 lists the models.

Table 2

Model descriptions

Model	Description

Model 0	Null model. The model assumes $E = 0$ and $\alpha = 1$ for the two tasks.
Model 1	The model assumes shared E and α for the two tasks.
Model 2	The model assumes shared α but separate E for the two tasks.
Model 3	The model assumes shared E but separate α for the two tasks.
Model 4	The model assumes separate E and α for the two tasks.

2.8 Model Comparison

The model comparison relies on the widely applicable information criterion, also known as the Watanabe – Akaike information criterion (WAIC), to account for the differences in the number of model parameters. The WAIC assesses the accuracy of a given model to predict the entire sequence of choices in one task based on the estimated parameters. Priors used in each model are shown in Table 3. Note that priors for Models 1 to 4 were uniformly distributed because E and α may be different for each participant and each value from the set range were equally probable. Both priors for E and α starts from zero. The prior for E had to cover all reward-probability combinations shown to the participants. Priors in α doesn't have a theoretical upper bound, but the effect in scaling the subjective utility for choice behavior plateaus and doesn't change as much as α increases. On the other hand, since Model 0 is built for cases where there is no effort discounting and that participants made choice selections with reward-probability just as it is, E was tightly and normally distributed around 0 whereas α was tightly and normally distributed around 1. As a result there might be instances where a participant is fitted with a negative effort cost. However, due to the small magnitude that is close to zero, such effect is negligible. The model comparison with WAIC was done with the map2stan function from the Rethinking package in R.

Table 3

Priors used in each model

Models	Free parameters	Priors
Model 0	E	$E = N(0, 0.05)$
	α	$\alpha = N(1, 0.05)$
Model 1	E	$E \sim U(0, 5)$
	α	$\alpha \sim U(0, 10)$
Model 2	E_{EEfRT}	$E_{\text{EEfRT}} \sim U(0, 5)$
	E_{SGT}	$E_{SGT} \sim U(0, 5)$
	α	$\alpha \sim U(0, 10)$
Model 3	E	$E \sim U(0, 5)$
	α_{EEfRT}	$\alpha_{\text{EEfRT}} \sim U(0, 10)$
	α_{SGT}	$\alpha_{SGT} \sim U(0, 10)$
Model 4	E_{EEfRT}	$E_{\text{EEfRT}} \sim U(0, 5)$
	E_{SGT}	$E_{SGT} \sim U(0, 5)$
	α_{EEfRT}	$\alpha_{\text{EEfRT}} \sim U(0, 10)$
	α_{SGT}	$\alpha_{SGT} \sim U(0, 10)$

Note. E_{EEfRT} and α_{EEfRT} refer to E and α in EEfRT, whereas E_{SGT} and α_{SGT} refer to E and α in in SGT.

3. Results

3.1 Model comparison

For each participant, the models were ranked in an ascending order based on the WAIC obtained. The difference between each model's WAIC and the model with the lowest WAIC (top-ranked model) was computed, along with the standard error of the WAIC difference. Each WAIC difference was compared to its respective standard error. If the WAIC difference was smaller than its standard error, the models were considered to fit the data equally well. This allowed for the possibility that two (or more) models were statistically equally good at describing the data. As a principle of parsimony, when two models were statistically equally good at describing the data (with regards to penalized deviance), the simplest of competing theories, which in this case is the model with the smallest number of free parameters, was chosen to describe the effort cost and decision mechanism of that participant. This process is critical because negligible differences in the fit may be caused by a small difference in the posteriors of the parameters when assuming effort cost and decision mechanisms to be distinct across the two tasks. Table 4 shows the number of participants best-fitted by each model. The expanded version of Table 4 (Table A1 in the Appendix) shows the best-fitted models combinations when multiple models fit equally well and the number of participants for each combinations.

Table 4

Number of participants best-fitted by each model (expanded version of the same table is shown in the Appendix as Table A1). Number of participants under each risk conditions for the best-fitted models were the sum of particpants from the model combinations in Table A1.

Best-fitted models	Risk		
	Low	Medium	High
Model 0	5	4	7
Model 1	24	21	16
Model 2	4	8	6
Model 3	1	3	6

Model 4	3	3	5
Model 2,3,4	3	4	0
Total	40	43	40

Note. All other model combinations had 0 participant counts.

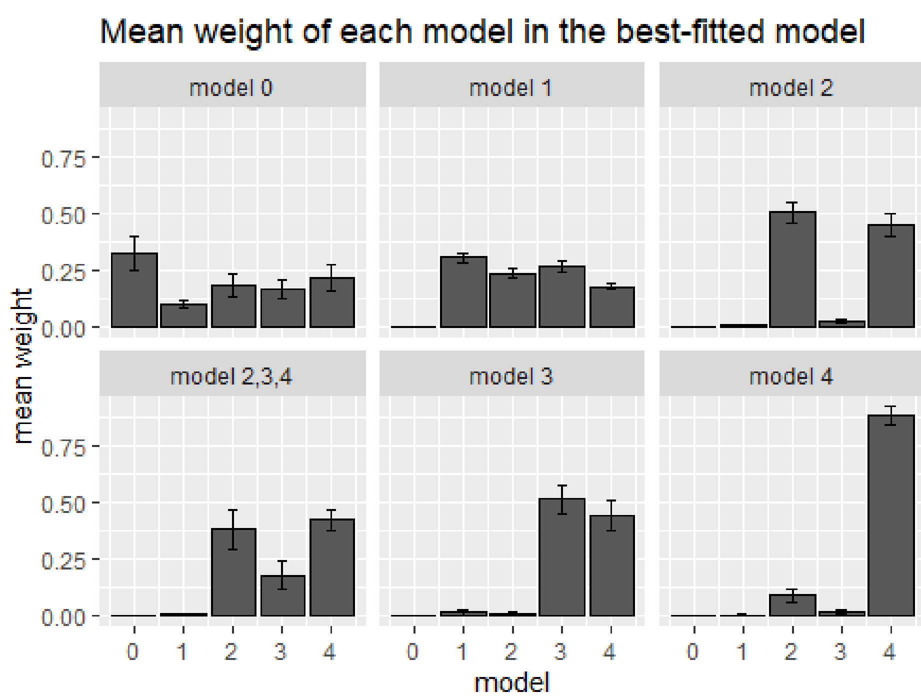
As can be seen in Table 4, the data from 16 participants (about 13%) were best described by Model 0 which assumed that the participant's choice selection was driven solely by reward and probability of winning the reward, and the harder trials were not perceived as more effortful than the easy choices. These participants were mostly indifferent about the task demand in the hard and easy choices. This may be a limitation of the EEfRT which also affects the SGT because it was calibrated to match choices in the EEfRT. This limitation in the present design is discussed in a later section.

The remaining 107 participants (87%) perceived the difference in effort cost across the hard and easy choices. Most of these participants (61 participants) were best fitted by Model 1, which may suggest common mechanisms for cognitive and physical tasks in processing effort cost and decision stochasticity. Eighteen participants were best fitted by Model 2 (separate effort costs but common decision stochasticity), 10 participants were best fitted by Model 3 (common effort cost but separate decision stochasticity), and 11 participants were best fitted by Model 4 (separate effort cost and decision stochasticity). The choice selections of 7 participants were equally well fitted with models 2, 3, and 4. Since models 2 and 3 have the same number of free parameters that are less than Model 4 and that they were contradictory to each other, no conclusion can yet be reached for these participants. Models 2, 3 and 4 required choice selection to be facilitated by the subjective utility with at least one separate mechanism for the effort cost or decision stochasticity in the two tasks.

Given the combinations of equally good models in describing the participant's data and how the best-fitted models were selected, we next computed the model weights. The model weights are a normalized version of how well each model fits the data, with the weights summing to 1. The mean model weights across subjects included in each row of Table 4 is shown as a separate panel in Figure 3. As can be seen, the best-fitted model in each panel has the highest mean weight. For example, in the panel of model 0, model 0 has the highest mean weight. Similarly, the mean weight of model 1 is the highest in the model 1 panel. All but the model 2, 3, and 4 panel (bottom left) showed the highest mean weight in the model that corresponds to the best-fitted model. In this panel, both model 2 and 4 have higher mean weights then model 3. Thus, with model 2 being more parsimonious than model 4, model 2 was selected as the best-fitted model to describe the effort discounting behavior in these participants.

Figure 3

Contribution of each model's weight in the best-fitted model from Table 4.



3.2 Comparing choice selection across participants best fitted by different models

Participants' choices and performance may be possible factors driving the discounting differences across the two tasks. Lower effort cost may be seen in participants that select hard choices frequently. On the other hand, decisions may be random in participants with high choice stochasticity, which may result in a 50-50 choice preferences, or choice preferences that do not follow subjective utility. In other words, influence of effort cost on choice preference is low in participants with high choice stochasticity. Task performance, which is often associated with task difficulty or demand, may be a driving factor for choice preferences. Table 5 shows the number of hard choices participants made for each task, separated by the best fitted model. Paired *t*-tests were computed to test whether the number of hard choices participants made in the two tasks differed. This analysis was performed separately for participants best fitted by each model. No significant differences were observed between tasks in participants best fitted with Model 1 ($t(60) = -0.852, p = 0.398, d = 0.046$), Model 4 ($t(10) = -1.473, p = 0.172, d = 0.707$), Model 2,3,4 ($t(6) = -0.413, p = 0.694, d = 0.163$), and Model 0 ($t(15) = -1.356, p = 0.195, d = 0.457$). However, participants that were best fitted with Model 3 ($t(9) = -3.219, p = 0.011, d = 0.760$) chose hard choice more often in the SGT than in the EEfRT. Although the difference was not significant, participants best fitted with Model 2 ($t(24) = -2.015, p = 0.055, d = 0.493$) trended towards selecting more hard choices in the SGT than in the EEfRT.

Table 5

Percentage of hard choice selection in the EEfRT and the SGT for each best fitted model

Best fitted model	EEfRT		SGT	
	Mean, %	Standard deviation, %	Mean, %	Standard deviation, %

0	71.9	10.4	77.5	13.8
1	55.4	23.9	56.4	23.9
2 + (2,3,4)	50.0	23.9	62.8	27.7
3	65.6	18.6	77.9	13.1
4	42.1	16.4	57.9	26.9
All models	56.1	22.8	62.4	24.4

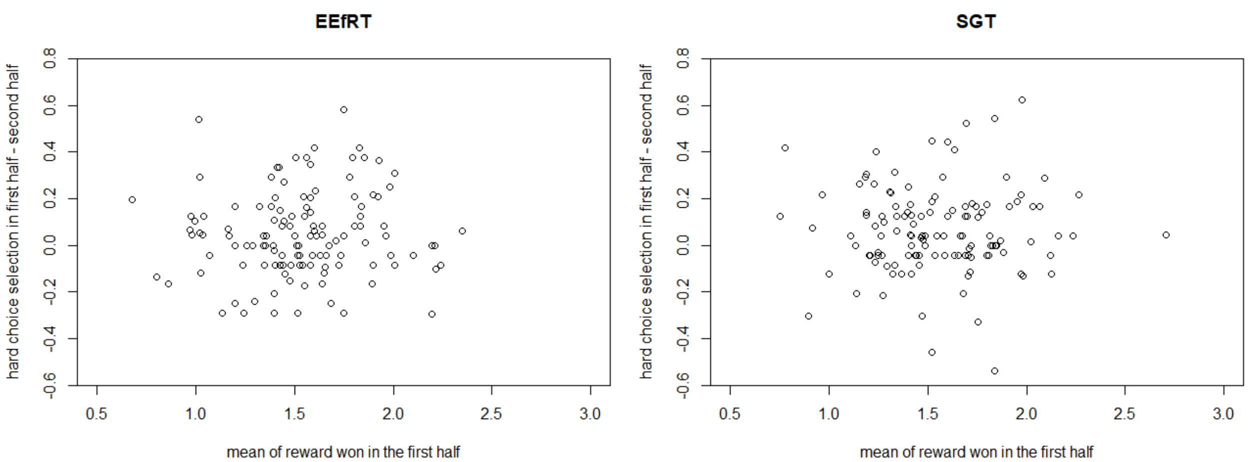
3.2.1 Order effects

Next, possible order effects of choice selection in the experiment and changes in choice selection across trials in each task were investigated. We failed to detect order effects for choice selection in either tasks (EEfRT: $t(121) = 0.501, p = 0.618, d = 0.090$, SGT: $t(121) = 0.907,\ p = 0.366,\ d = 0.164$). This suggests that we did not find evidence that the choices made in the two tasks were affected by the order of which task came first. However, when examining trials in the first half vs the second half of each task, choice selection changed as the task progressed (EEfRT: $t(122) = 3.064, p = 0.002, d = 0.276$; SGT: $t(122) = 3.862, p < 0.001, d = 0.348$), whereby participants chose more hard trials in the second half of the task than the first. While there may be different factors causing this effect, three possibilities we focused on were reward satisfaction, fatigue, and the knowledge gained on the reward structure as the task progressed.

The effect of reward satisfaction as shown in Figure 4 was determined by looking at whether the choice difference across trials was driven by the satisfaction of gathering enough rewards in the first half of the experiment. The mean of the rewards won in the first half of each task gave us a sense of reward satisfaction while the difference in proportion of hard choices made in the first and the second halves of the tasks implies if participants made more (or less) choice in the second half of the task. The effect of reward satisfaction may be seen if fewer hard choice were made when the reward obtained in the first half was greater. However, there was no significant correlation between the mean reward won in the first half of the tasks and the difference in proportion of hard choices made in the first and second halves of the experiment (EEfRT: $R^2 = 0.042, p = 0.642$; SGT: $R^2 = 0.009, p = 0.926$).

Figure 4

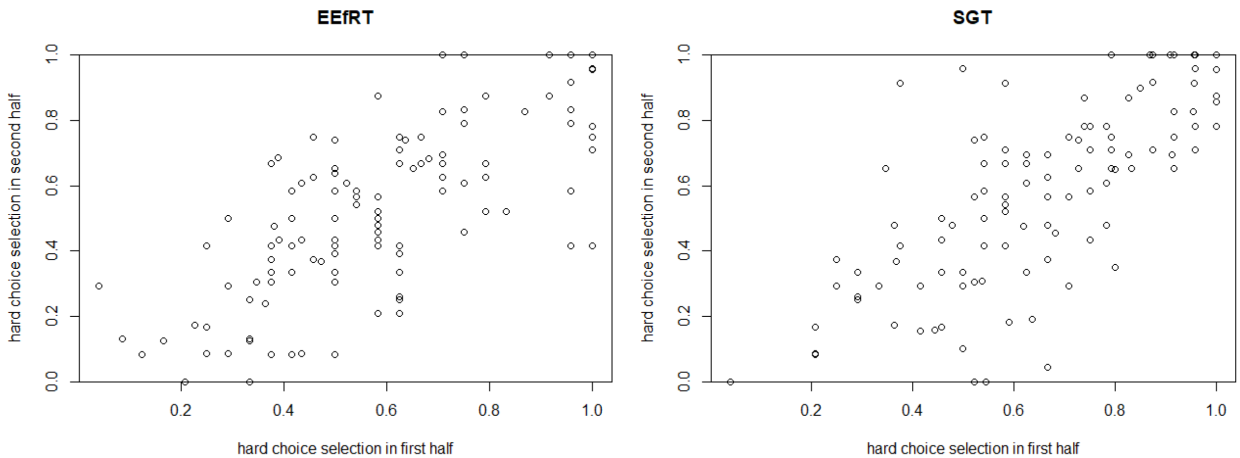
The relationship between the mean of reward won in the first half of the task and the difference in proportion of hard choices made in the first and second halves of the task (left: EEfRT, right: SGT).



The effect of fatigue may be observed if participants that chose hard choices more at first made fewer hard choices towards the end of the task. Thus, fatigue should be accompanied by a negative correlation between the hard choices made in the first half and the second half of each task. However, this was not the case as shown in Figure 5, with positive correlations shown comparing the proportion of hard choices made in the first and second halves of both tasks (EEfRT: $R^2 = 0.731, p < 0.001$; SGT: $R^2 = 0.766, p < 0.001$). The positive correlation implies that if a participant chose more hard choices in the first half of the task, the same participant also chose more hard choices in the second half of the task, which is the opposite of the fatigue effect.

Figure 5

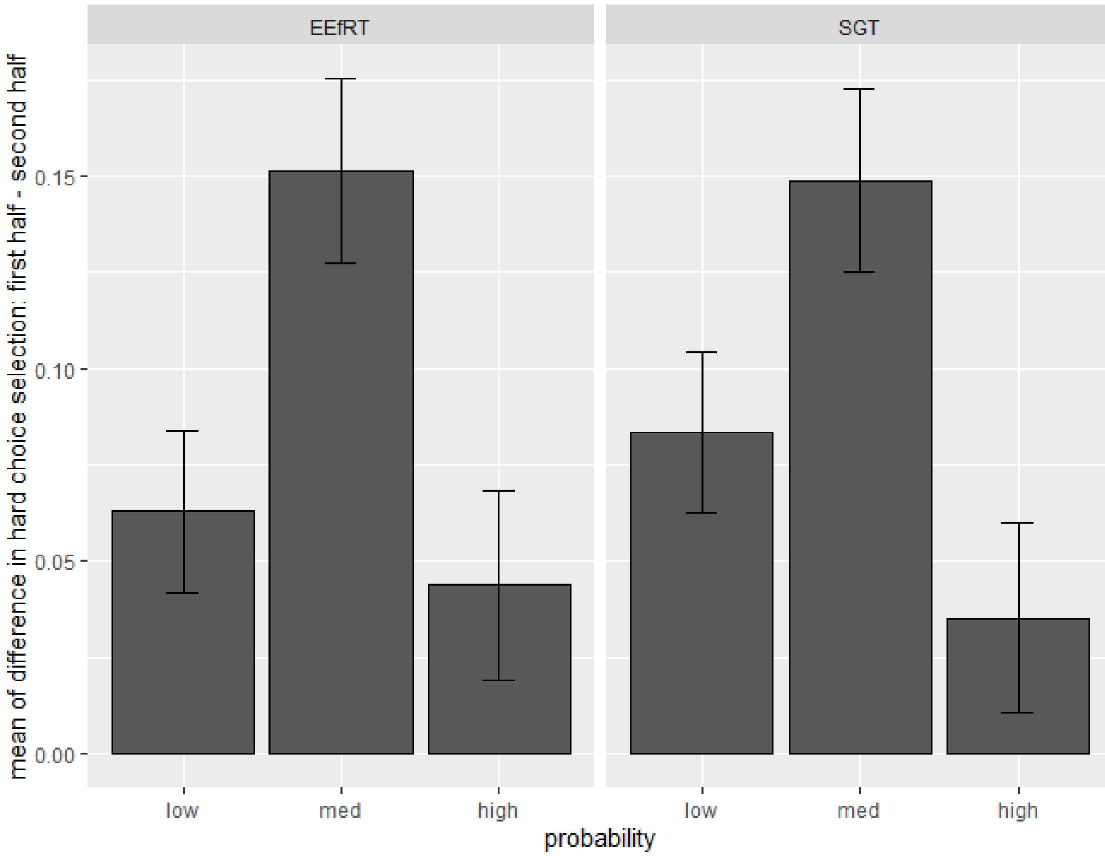
The proportion of hard choices made in the first and second halves of the task (left: EEfRT and right: SGT).



With fatigue and reward satisfaction out of the picture, we examined whether figuring out the reward structure at a later stage of the task influenced choice differences across trials. One possible factor is the experience of win-probability. The choice difference across the tasks for the three levels of probabilities shown to the participants are depicted in Figure 6. The three levels of probabilities were the low ($p(t)$ = 0.00, 0.12, or 0.24), medium ($p(t)$ = 0.38, 0.50, or 0.62) and high ($p(t)$ = 0.76, 0.88, or 1.00) win-probabilities shown to the participants, regardless of the risk-condition. Testing the difference in number of hard choices made in the first and second halves of the task against zero, participants in the EEfRT made fewer hard choices in the second half of the task when the probability of winning the reward was either medium ($t(122) = 6.33, p < 0.001, d = 0.498$) or low ($t(122) = 3.002, p = 0.003, d = 0.187$). No significant difference was observed for the difference in number of hard choices when the probability of winning the rewards was high ($t(122) = 1.789, p = 0.076, d = 0.156$). In the SGT, participants made fewer hard choices in the second half of the task when the probability of winning the reward was either medium ($t(122) = 6.352, p =< 0.001, d = 0.573$) or low ($t(122) = 3.074, p = 0.003, d = 0.227$). Similar to the EEfRT, no significant difference was observed for the difference in number of hard choices when the probability of winning the rewards was high ($t(122) = 1.739, p = 0.085, d = 0.138$). Together, these results suggest that participants may engage in choice exploration at the beginning of the task, but as the task progresses and after experiencing the win-probability, the participants chose the hard choice less when the win-probability shown was low or medium. This interpretation would be consistent with earlier work suggesting that participants aim at minimizing effort when reward is unlikely (Kool et al., 2010). Thus, learning the win-probability may account for how choice selection changed as the task progressed..

Figure 4

Choice difference across task for the three levels of probabilities shown to the participants (left: EEfRT, right: SGT). The choice differences across task was calculated by taking the mean of the difference in the numbers of hard choices made in the first and second halves of the tasks.



3.3 <u>Comparing task accuracy across participants best fitted by different models</u>

Table 6 shows mean accuracies in easy and hard choices separated by task and best fitted model. Paired t-tests were computed to test whether the accuracy in hard and easy choices differed between the two tasks. This analysis was performed separately for participants with each best fitted model. Because some participants chose the hard choice for all trials in at least one of the tasks, data from these participants were omitted in the comparison of accuracy for easy choices across the EEfRT and SGT (n = 5). For hard choices, participants best fitted with Model 1 performed significantly better in the EEfRT as compared to the SGT, $t(60) = 2.654, p = 0.010, d = 0.465$. However, no significant difference in accuracy was observed for participants that were best fitted with Model 2 ($t(24) = 1.737, p = 0.095, d = 0.416$), Model 3 ($t(9) = 0.366, p = 0.723, d = 0.168$), Model 4 ($t(10) = -0.760, p = 0.465, d = 0.345$), and Model 0 ($t(15) =$

$1.269, p = 0.224, d = 0.452$). Similarly, for easy choices, participants best fitted with Model 1 performed significantly better in the EEfRT as compared to the SGT, $t(56) = 3.759, p < 0.001, d = 0.620$. Again, no significant difference in accuracy was observed for participants that were best fitted with Model 2 ($t(23) = -0.283, p = 0.780, d = 0.050$), Model 3 ($t(9) = -0.059, p = 0.954, d = 0.030$), Model 4 ($t(10) = 0.638, p = 0.538, d = 0.298$), and Model 0 ($t(15) = -0.109, p = 0.914, d = 0.035$).

Table 6

Mean accuracy (and SD) of easy and hard choices in the EefRT and SGT for each best fitted model

Best fitted model	Accuracy, % (standard deviation)			
	EEfRT		SGT	
	Easy choices	Hard choices	Easy choices	Hard choices
0	90.6 (9.2)	87.9 (15.7)	91.0 (13.0)	81.6 (12.2)
1	93.0 (13.3)	87.4(20.0)	81.9 (21.7)	78.5 (18.5)
2 + (2,3,4)	92.8 (12.1)	91.8 (17.4)	93.4 (12.0)	85.3 (13.6)
3	91.1 (16.4)	88.3 (31.1)	91.5 (15.2)	84.4 (10.2)
4	92.2 (8.3)	77.6 (38.5)	86.6 (25.1)	87.57 (13.4)
All models	92.4 (12.4)	87.6 (22.2)	86.7 (19.3)	81.6 (16.0)

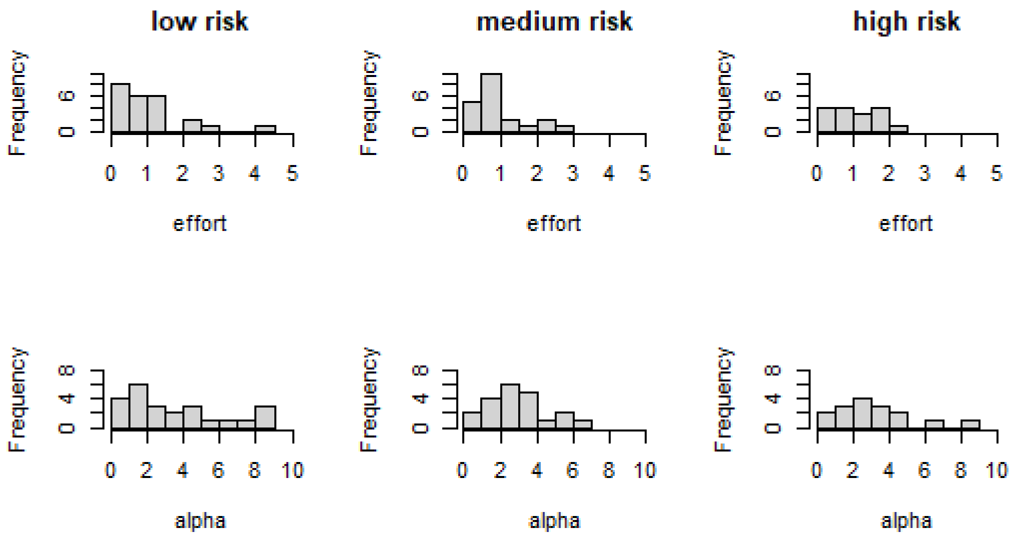
3.4 Testing task stability with different risk-incentive combinations

A chi-square test of independence was performed to examine the relation between best fitted model and risk condition. The relation between these variables was not significant, $X^2(10, N = 123) = 11.034, p = 0.355$. As a result, the influence of risk condition on the number of participants best-fitted by each model was not observed. Figure 8 shows the distribution of

E and α for participants of different risk conditions who were best fitted by Model 1 (about half of the participants). In the low-risk condition, E averaged at 0.961 (standard deviation = 1.021) and α averaged at 3.593 (standard deviation = 2.719). In the medium-risk condition, E averaged at 0.941 (standard deviation = 0.747) and α averaged at 2.813 (standard deviation = 1.642). In the high-risk condition, E averaged at 1.086 (standard deviation = 0.693) and α averaged at 3.018 (standard deviation = 2.188). From Figure 7, it seems that E for the low risk condition had a greater positive skewness (skewness = 1.504) when compared to the higher risk conditions (skewness in medium risk = 0.876, skewness in high risk = 0.171). The greater positive skewness in E in the low risk condition indicates that more participants in the low risk condition have a smaller effort cost. However, this may be due to the scaling effect of effort with reward when computing the subjective utility, which results in a lower effort cost as compared to the other risk conditions. In contrast, the α for the high risk condition had a greater positive skewness (skewness = 1.119) when compared to the lower risk conditions (skewness in low risk = 0.623, skewness in medium risk = 0.533). The greater positive skewness in α in the high risk condition indicates that participant followed the subjective utility less strictly in the high risk condition where the win probability is low.

Figure 7

The distribution of the maximum a. posteriori of E (top row) and α (bottom row) for all participants best-fitted with Model 1 under different risk conditions.

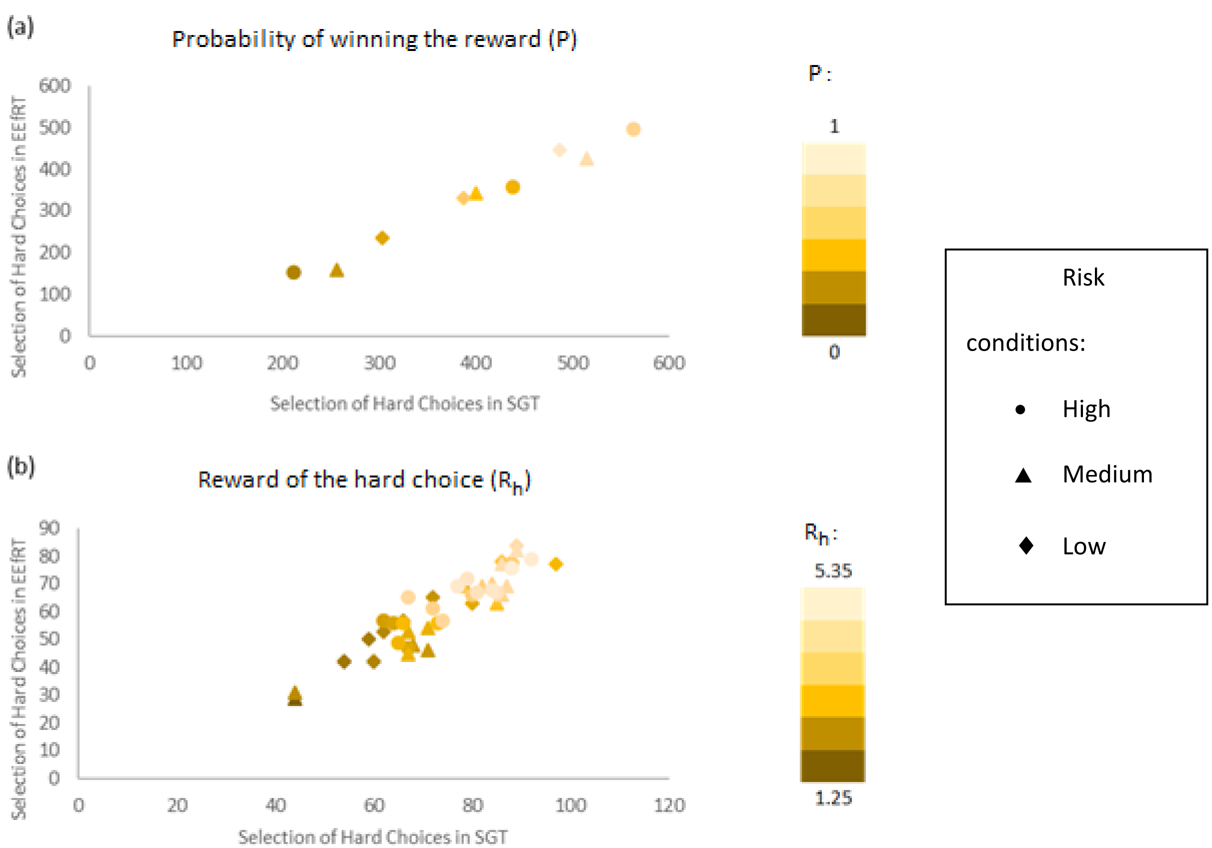


3.5 Sensitivity to changes in reward motivation

Because about half of the participants were best fitted with Model 1, where the same E and α were utilized for choice selection in the two tasks, the influence of decision factors, namely the reward and win-probabilities on choice selection, were investigated next. This is to explore whether the two measures were similarly sensitive to changes in reward motivation in both tasks. To explore how reward affects choice selection in the two tasks, the number of hard choice selection for all participants (regardless of the model fit) was computed with respect to the reward shown. This was done separately for the two tasks. Similarly, to explore how probability of winning the reward affected choice selection in the two tasks, the same was computed with respect to the probability of winning the reward for the EEfRT and the SGT separately. Figure 8 compares the number of hard choices in the two tasks for different magnitudes of rewards and probabilities. As can be seen, choice selection in one task is positively and highly correlated to the choice selection in the other task across different reward values ($R^2 = 0.83, p < 0.001$) and probabilites of winning the reward ($R^2 = 0.98, p < 0.001$). Moreover, the positioning of the color codes in the graphs suggested that more hard choices were made when reward and probability of winning the reward were high. This is consistent with their role in increasing choice utility in the proposed models: participants were more willing to exert extra effort in choosing the hard choices of the tasks when the reward and probability of winning the reward were high.

Figure 8

The frequency with which participants selected the harder task in the EEfRT (y-axis) and the SGT (x-axis) with respect to the differences in (a) the probability of winning the reward and (b) the reward value presented in the three risk conditions



Note. Each symbol in the top panel represents one of the nine win-probabilites while each symbol in the bottom panel represents one of the 48 rewards shown to the participants. Symbol color corresponds to reward or probability values and shape corresponds to risk condition.

4. Discussion

We proposed the use of the SGT as a cognitive-based alternative to the EEfRT and showed similar effort discounting in choice selection in the EEfRT and the SGT. By comparing action selection under different reward motivation between the SGT and the EEfRT, we showed that individual differences in cognitive and physical effort discounting can be accounted for by common mechanisms. By computing the subjective utility in the two tasks, we proposed the use of computational models as an indirect measure of cognitive effort by relating the subjective cognitive effort to physical effort. With the quantification of cognitive effort in the SGT, the use and study of effort discounting can be broadened to reward motivation-based decision-making, especially in clinical populations.

The best-fitting model with the most participants was a model that assumed shared effort cost and choice stochasticity across the two tasks. This suggests that the relative effort cost in choosing the harder version of the task for greater rewards was perceived similarly in both tasks by many participants. The shared effort costs in these participants were reflected as similar proportions of hard choices made in the two tasks. This shows that participants perceived similar effort costs in the SGT and the EEfRT, and that the effort cost reduced the expected value of the options presented in the task. Choice selection in participants who have lower choice stochasticity (higher α) were driven more by subjective utility. Thus, with greater certainty in obtaining a greater reward, participants were more willing to invest effort to optimize reward in both the SGT and EEfRT.

It should be noted that about 13% of participants were best described by Model 0, whereby effort cost did not influence choice utility, and the stochasticity parameter, α had a low value. These participants had a lower effort cost and did not scale the utility of the tasks. Because these participants did not show a difference in effort perception between the easy and hard versions of the tasks, the task demand did not influence their choice selection. These participants generally had a greater choice preference towards the hard choices, as the objective utility of the hard choice was always greater than the easy choice. They would only choose the easy choice when the perceived subjective utility of the easy choice was about the same or greater than the hard choice. Since these participants also share similar effort discounting across the two tasks, they selected hard choices about the same number of times in both the SGT and the EEfRT. Fatigue may be one of the factors contributing to this observation, but this was not explicitly tested in the present experiment. Further investigation is needed to explore what drives the difference in hard choice selections in the two tasks in this group of participants.

4.1 Measuring cognitive effort

It was shown that the data from most participants in different risk conditions was best-fit by Model 1, which showed that the effort cost and the reliance of subjective utility in choice selection remained the same across tasks. Moreover, regardless of whether the participant was risk averse or risk seeking, the change in task did not change the participant's behavior and risk-reward perception. Since the effort cost was shown as a stable trait across tasks in the majority of participants, this study demonstrated the possibility of using the SGT as an alternative to the EEfRT in examining effort-based decision-making. Model fitting was not affected by varying the overall reward and risk of winning the reward. However, effort cost and choice stochasticity may be influenced by the risk condition. The distributions of α and E across the different risk conditions were skewed positively. The greater positive skewness in E in the low risk condition may be due to the scaling effect of effort with reward when computing the subjective utility. The greater positive skewness in α in the high risk conditions may be due to the greater uncertainty in obtaining the reward, whereby more participants relied less to the subjective utility in choice selection.

However, in about 37% of the participants, either the effort cost or the participant's reliance on subjective utility in choice selection may be different (fitted separately but values may coincide) for the two tasks. Around 20% of the participants may have perceived different effort costs in the two tasks but the influence of subjective utility on choice selection was similar in the two tasks. These participants tended to choose the hard version of the task more in the SGT as compared to the EEfRT. The lack of a significant difference between tasks for these participants may have been due to the small sample size. The difference in perceived effort cost may be a potential factor driving this trend towards a significant difference. These participants may have perceived a greater effort cost in the EEfRT. The difference in effort cost may be driven by the trending difference in their performance in the hard trials of the two tasks, whereby the performance in the hard trials in the EEfRT was better than in the SGT. In the SGT, with less uncertainty in obtaining the reward (existing probability shown and performance uncertainty), the participant might make more hard choices to increase their chances of obtaining the reward. Previous studies comparing cognitive and physical effort showed that people are more willing to exert effort for a lower reward and chance of receiving the reward in a cognitive effort-based decision paradigm when compared to the EEfRT, even when they deemed the cognitive task to be more difficult (Lopez-Gamundi & Wardle, 2018). However, task difficulty does not directly translate into effort (Kool & Botvinick, 2018). Future research should examine the task preferences of individuals between the SGT and the EEfRT by allowing participants to choose between the two tasks in each trial with varying task demands (Potts et al., 2018) and reward offers. Moreover, the tasks can be modified to personalize and calibrate the task demands and fit to each participant's performance.

On the other hand, subjective utility in the two tasks were not perceived or utilized equally in about 17% of the participants. Among these participants, about half of them had a similar effort cost in both tasks, and the other half perceived different effort costs in the two tasks. The former participants made more hard choices in the SGT than they did in the EEfRT, while the latter's choice selection in both tasks wasn't dissimilar. It is noted that no significant difference was found when comparing performance in both tasks for these participants. The difference in effort cost moves motivation either up or down, while the difference in choice stochasticity scales motivation by either amplifying subjective utility or blurring motivation to choose by chance. It is highly possible that choice selections in participants who perceived unequal subjective utility but similar effort cost across the two tasks may have been driven by order effects, such that the participants chose the hard choice more often in the task that came first as compared to the task that came after. However, we could not examine the possibility of order effects in these participants due to small sample size. Possible factors causing the order effect may include a lack of understanding of the experiment at the start of the task, or even as a result of forming strategies after the first task. On the other hand, choice selection in participants that perceived both subjective utility and effort cost differently in the two tasks may be driven by a lack of difference in the perceived difficulty of accomplishing the hard and easy trials, especially in the SGT. Effort cost or even choice stochasticity may not be the same in the two tasks if one task was perceived as more demanding than the other task.

4.2 Possible applications for the proposed SGT

With the EEfRT's contribution in showing decreased motivation for rewards in trait anhedonia (Treadway et al., 2009), and the significant prior evidence linking mesolimbic dopaminergic systems to symptoms of anhedonia in depression (Phillips et al., 2007; Salamone & Correa, 2002), the proposed cognitive paradigm may be applicable to study how depletion of dopamine in the nucleus accumbens is associated with decreased motivated behaviors toward "wanting" a desired goal (Berridge and Robinson, 1998). The neurotransmitter dopamine has been shown to aid in overcoming choice response costs and to increase the selection of effortful actions (Salamone and Correa, 2002; Phillips et al., 2007) in various domains of effort (Cools, 2015; McGuigan et al., 2019; Verguts et al., 2015; Westbrook & Braver, 2016). Furthermore, given that about 40% of patients with Parkinson's disease (who have reduced dopamine levels; Damier et al., 1999) have symptoms of motivational disorders in addition to motor deficits (den Brok *et al.*, 2015), the proposed cognitive paradigm may be an alternative in examining the motivational deficits in incentivized decision-making involving people with Parkinson's disease. The SGT may benefit such studies even more given the disorder of movement in people with Parkinson's disease. For these participants, constant physical effort tasks may be deemed extra effortful with a greater sense of effort related to fatigue (Solomon and Robin, 2005). As a result, perception of effort expenditure in physical effort-based decision-making tasks may be much greater in people with Parkinson's disease.

Despite the clinical importance of studies of reward motivation, there is still a large gap in knowledge about effort-related decision-making in humans. Thus, we propose the use of a cognitive task to measure the willingness to exert effort in cognitive decision-making that is comparable to the existing EEfRT (Lopez-Gamundi & Wardle, 2018). Such a task will not only be beneficial in studying the discounting effect in motivational decision-making, it may also contribute to the comparison of the role of dopamine in manipulating the willingness to exert effort in cognitive and motor domains.

4.3 On the relation between cognitive and physical effort

In the present study, the cognitive effort to accomplish the SGT was attention-based, where participants had to track the movement of the target without being distracted by the motion of the distractor items. This sustained attention was not needed in the EEfRT, since the EEfRT only required participants to repeatedly press a key. Despite the difference in the nature of effort expenditure, reward motivation of the majority of participants were discounted similarly for the two tasks. The similarity in effort discounting with both physical effort and sustained attention may thus be a general phenomenon across many cognitive functions. More research is needed to explore the generality of these results.

Sustained attention can be associated with different or perhaps opposite subjective effort experiences. Humans tend to mind wander or even avoid engagement in repetitive and uninteresting tasks, yet are fully absorbed in tasks that they find interesting but equally cognitively demanding (Csikszentmihalyi, 1975; Langner & Eickhoff, 2013). Sustaining attention to simple, intellectually unchallenging, monotonous tasks is perceived as effortful and demanding (Kahneman, 1973; Manly et al., 2003). Extended performance in such situations may lead to subjective strain or even cognitive fatigue over time (Grier et al., 2003; Langner & Eickhoff, 2013; Warm et al., 2008), and is often associated with increased absentmindedness and mind wandering (Cheyne et al., 2009; Langner & Eickhoff, 2013; Smallwood et al., 2004). The SGT is an example of such a simple, monotonous, and repetitive task that requires participant to sustain attention on the target. Because it may induce cognitive fatigue over time, it is parallel and translational to the

EEfRT that incudes physical fatigue. As a result, the SGT is suitable for studying the breakeven of sustained attention-induced cognitive effort with increased reward motivation without adding unwanted confounding factors of motivations such as those from the challenging tasks.

With showing how effort exertion is comparable in the SGT and the EEfRT, this study also suggests a possibility for an indirect measurement of cognitive effort through computing the effort cost with the computational models presented. Since the effort exertion or work done in key-pressing can be measured in Joules, by equating the effort in the SGT and the EEfRT, it may be possible to obtain a rough estimation of effort perception analogous to Joules for a cognitive task such as the SGT. This could be useful in the quantification of cognitive effort because estimating effort exertion in a cognitive paradigm has proven to be difficult. More work is needed to test for this possibility.

4.4 Limitations

One potential concern in the experiment is the issue of temporal discounting in the tasks. In the EEfRT, with the difference of the trial's time limit and number of key presses between the easy and the hard choices, participants may take a longer time to finish the hard choices as compared to the easy choices. On the other hand, in the SGT, there are more swapping in the hard choices than the easy choices, even with the increased speed in the hard choices, the time to complete one trial when choosing the hard choice is longer than that when choosing the easy choice. The issue of time may be confounded with the effort cost in affecting the choice selection. The original EEfRT (Treadway et al., 2009) was designed to serve as an objective measure of individual differences in reward motivation, in assessing the willingness to make choices that require greater effort in exchange for greater reward. The hard choice in the EEfRT requires extra (often twice as much or more) motoric or physical work as compared to the easy choice. However, heavier work is often accompanied by possibly longer time in accomplishing the work and a greater uncertainty of success. This leaves the nature of discounting in EEfRT not purely demand-related, temporal discounting or even uncertainty in accomplishing the task may be influencing the choice selection. It should be noted that prolonged motoric work may seem extra effortful (Cos, 2017; Morel et al., 2017), and it is hard to distinguish the effect of physical effort discounting or temporal discounting in such cases. Past research had shown the effects of poor quality of sleep on the preference for hard choices in the EEfRT but not on delay-discounting for greater reward that participants need to wait longer to obtain (Boland *et al.*, 2022). This suggests that the discounting cost in the EEfRT is not solely based on temporal or delay-discounting. Moreover, in our study, participants were informed that they would only receive the reward towards the end of the experiment, once all participants in the same session were done with both tasks. This should minimize temporal discounting effects on reward motivation for both tasks. In addition, the hard choices were selected for more than half of the time of the tasks. This means that most participants were not rushing through the experiment by selecting the easy choice only.

A study from Giustiniani et al. (2020) measured event-related potentials associated with reward processing in a modified version of the EEfRT. In their version of EEfRT, participants had to reach 70% of their maximum number of key presses in 7s if they chose the easy or less demanding choice, and 90% of their maximum number of key presses in 14s for the hard or more demanding trials. With a much lower speed of key presses in the hard trials, which compensates for the greater uncertainty of accomplishing the task, they managed to replicate the results from the original EEfRT in demonstrating that participants chose to press more keys when the reward motivation is high.

Furthermore, accuracy in both the hard and easy choices in the SGT was significantly lower than that in the EEfRT. Even though the demand in each task was adjusted based on the accuracy in pilot experiments, it can still vary across participants in the actual experiment. Future studies may require adjusting the difficulty metrics in the tasks. It should be noted that this difference in accuracy may pose a problem when comparing the two tasks, but should not be a problem when using the individual tasks. The SGT can still capture the devaluation of motivation with the difference in task demand.

The current study only showed the possibility of relating sustained-attention based cognitive effort to physical effort. More work is needed to determine when the effort discounting effect differs in the two types of effort tasks. Functional MRI (fMRI) studies have shown shared neural bases for cognitive and physical effort discounting in humans, along with certain task-specific regions (Schmidt et al., 2012). Specifically, the ventral striatum has been shown to serve as a general motivational node in driving both the cognitive and motor regions of the dorsal striatum (Schmidt et al., 2012). Future studies can be conducted to determine if differences in the activation of neural correlates can account for differences in effort discounting. One possible experiment is to examine if an individual weighs reward and risk equally in the two types of effort motivation. The results presented in this article showed that choice selection may be driven by utility in a similar way across the two tasks. However, the influence of reward and the probability of winning the reward on the choice selection were not explored separately. Relating the differences (if any) in the choice stochasticity by reward and risk to the differences in neural correlates may help understand the discrepancies in effort discounting in the two types of effort. Furthermore, with the difference in effort distribution observed across different risk conditions, the effect of reward in effort perception can be further investigated.

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Appendix

Table A1

Expanded model information for Table 4: Number of participants best-fitted by each model combination. For example, the combination of model 0, models 0 and 2, models 0 and 3, up to models 0, 1, 2, 3 and 4 all include model 0 as equally good in describing the participant's behavior. Thus, model 0 was selected as the best-fitted model under the principle of parsimony with Occam's razor.

Best fitted models	Risk		
	Low	Medium	High
Model 0:			
0	0	0	2
0,2	0	1	0
0,3	0	1	2
0,1,2	0	1	1
0,1,3	1	0	0
0,2,4	1	0	0
0,1,2,3	1	0	0
0,1,3,4	0	0	1
0,2,3,4	1	0	1
0,1,2,3,4	1	1	0
Model 1:			
1	7	3	3
1,2	2	2	3

1,3	2	3	2
1,4	1	0	0
1,2,3	4	5	3
1,2,4	2	0	0
1,3,4	2	1	2
1,2,3,4	4	7	3
Model 2:			
2	1	5	1
2,4	3	3	5
Model 3:			
3	0	1	2
3,4	1	2	4
Model 4:			
4	3	3	5
Model 2 or Model 3:			
2,**3**,4	3	4	0
Total	40	43	40

Note. All other model combinations had 0 participant counts. Bold model numbers are the corresponding selected model in Table 4.