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Effort-based Delay Discounting: A Novel Mechanism for Understanding Willpower Failures in Goal-oriented Decision Making

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ABSTRACT

Willpower failures in real-life goal-directed conflicts are characterized by decisions to engage in low-effort immediate rewards over effortful actions with delayed benefits. While intertemporal choice paradigms have extensively examined how delays discount rewards, the influence of concurrent effort demands on decision-making remain unexplored. We developed a novel Effort-based Delay Discounting paradigm to assess the integrated influence of delay and cognitive effort on subjective value, and to derive a model-free behavioural index of this combined discounting. Sixty-two healthy adults completed an Effort-based Delay Discounting task combining three levels of cognitive load (n-back: 2-back, 3-back, 4-back) with six temporal delays (1–180 days), making 144 incentivised choices for real monetary rewards. Linear mixed modelling revealed a significant effort × delay interaction: higher cognitive effort demands systematically attenuated the gradient of delay discounting by 42%, compressing sensitivity to temporal distance. This pattern persists after controlling for task performance, indicating genuine motivational dynamics rather than cognitive constraints. Volume Under Surface (VUS), a model-free index of combined discounting, showed substantial individual variability and discriminant validity from trait willpower measures. These findings reframe willpower failures as failures of integrative cost weighting under concurrent demands, with implications for understanding goal-directed motivation and designing interventions targeting context-dependent decision-making vulnerabilities.

Keywords: willpower, effort discounting, delay discounting, COG-ED, value-based decision making, reward valuation

Introduction

In situations when we have to choose between an immediate temptation and a long term goal, it becomes very difficult for the individual to persist in their goal-pursuit, for they become susceptible to lapses in their inhibitory-control mechanisms (Sukumar et al., 2022). Researchers use terms like ‘lack of self-control’, ‘motivational deficits’ and particularly ‘failure of willpower’ to describe the behavioural outcomes of such decisions (Baumeister et al., 2024; Werner & Berkman, 2024). However, this tendency to yield to the hedonic alternative is common across many behavioural contexts ranging from addictions, pathological conditions to goal-oriented pursuits such as strength training and healthy eating (Barbosa et al., 2022; Cheng et al., 2021; Devoe et

al., 2022; Lee et al., 2019; Li et al., 2021). This incontinence in human behaviour demands a timely need for explaining such deviations from goal-pursuit, an issue which is centrally addressed by the concept of *willpower*.

Willpower is understood as the rational executive capacity enabling humans to resist impulsive urges and remain committed to their future goals by exerting cognitive control over shot-term temptations (Chislenko, 2023; Metcalfe & Mischel, 1999; Mischel et al., 2011). Contemporary psychology defines willpower as the ability to overcome immediate desires through deliberation and commitment in pursuit of long-term goals (Henden, 2008; Neal et al., 2013; Veilleux et al., 2021). However, over past two decades, empirical research has conflated willpower with adjacent constructs such as 'self-control', 'volition or voluntary action', 'mental effort' etc. under the broad umbrella of effortful self-regulation (Haggard 2008; Inzlicht et al. 2021; Wolpe et al. 2024). This has led to a sparse and fragmented understanding of the conceptual and operational nature of willpower. Consider a prototypical willpower scenario, choosing to study over scrolling social media requires resolving the conflict between momentary pleasure and a delayed benefit through deliberate allocation of cognitive resources, making it a fundamentally rational choice problem. This underscores not all self-control behaviours are self-regulatory in nature, nor are all impulsive behaviours indicative of willpower failure (Duckworth et al., 2018) which deems this conflation as a hinderance to advancement of willpower research. The element of choice and the context around such conflicts, which gives the individual agency over his goal-directed behaviour remains understudied. Over the years this construct has accumulated various renditions: as a limited capacity analogous to a muscle which gets stronger with prolonged use (Baumeister et al. 2018); as a stable personality trait enabling improved performance across lifespan (Mischel et al., 2011; Okan, 2025); and as a mechanism for motivated actions contingent on implicit beliefs (Bernecker & Job, 2017). Each of these frameworks capture an essential facet of willpower yet does not provide a reliable operational measure sufficient to characterize how it functions under realistic conditions of competing cost demands.

Decision theorists have argued that willpower is more granularly understood within value-based decision making models, where agents choose between viscerally motivated and deliberately desired alternatives by weighting their costs and benefits (Gold, 2018). This framing has been relevant in domains where willpower failures are more rampant and consequential like addiction recovery, gambling and health behaviours. Decision theoretic models highlight how individuals systematically underestimate the pull of visceral factors competing with higher goals (Loewenstein, 2000). Qualitative accounts of willpower drawn from sample navigating goal-oriented conflicts such as recovering patients, obese individuals managing weight and undergraduate students validate this framing. The thematic content of their reported experience is oriented more towards a deliberative

cost-benefit conflict than a failure of inhibitory capacity (Alexandersen et al., 2019; Crofton, 2021; Sweeney et al., 2019). In a seminal account Ainslie, (2020), formalized this by identifying two distinct facets of willpower; suppression and resolve which have a symbiotic relationship with controlling behavioural impulses in the trajectory of reaching a desired goal. He described how every willpower evoking situation, by default follows an intertemporal conflict where agent must choose between a smaller reward available immediately or a larger reward available in future (Read et al., 2018). Naturally individuals who fail to control their impulses end up choosing the smaller reward impulsively. Behaviours such as dieting, savings, physical exercise, relationships and habitual behaviours illustrate the impulsivity in choice as a result of devaluation of the future reward, known as delay discounting (Burns et al. 2007; Duff et al., 2024; Yi et al., 2010; Yin et al., 2022). However, apart from the temporal dimension of impulsivity, another major determinant of willpower-based conflicts, remain largely unexplored. The *effortfulness* of the task demand is an integral part of any self-regulation conflict which decides subsequent course of action (Dillen et al., 2012; Koole et al., 2012). Willpower failures are often observed in people who refuse to engage in doing effortful activities like dieting or strength training or even meditation, which have long-term benefits further highlighting the need to incorporate effort in delay gratification behaviours (Niebaum et al., 2025; Yanaoka et al., 2024). This paper aims to expand on the value-based framing of decisions in willpower evoking scenarios, by integrating influence of multiple decisional costs like delay and effort which lead to impulsive choices.

Integration of Decisional Costs in a Unidimensional Framework

Delay discounting patterns observed across individuals and contexts show that the subjective value of a future reward hyperbolically declines as a function of how long one must wait for the rewarding outcomes (Haith et al., 2012; Schultz, 2010). Neurobiologically, this devaluation is computed in dopaminergic and striatal systems, with the frontoparietal network and anterior cingulate cortex tracking the relative salience of delayed versus immediate alternatives (Cona et al., 2023; Soutschek et al., 2023). When delays are longer, people reverse their preferences and opt for smaller but immediately gratifying rewards, despite having the desire for having larger delayed alternative. This preference reversal is a direct behavioural marker of impulsive choice and highlights willpower failure in goal-directed behaviours (Chakraborty, 2021; Sharma & Khan, 2021). Delay, in this account is not merely an attribute of the reward but a computational cost that erodes value at each moment of waiting. Parallelly, effort also functions as a distinct cost in value-based decision-making influencing systematic devaluation of rewards that require effort expenditure to obtain, known as Effort discounting (Botvinick et al., 2009; Erfanian Abdoust et al., 2024). Effort is structurally different from delay due to its tangible immediacy.

Delays are representational as in the decision maker must mentally simulate the experience of waiting whereas effort is a present somatic demand felt directly at the moment of choice (Benoit et al., 2011; Escobar & Mitchell, 2025). Although effort takes different forms such as physical, cognitive, emotional etc. evidence consistently shows that these modalities converge on a domain-general valuation system (A. J. Culbreth et al., 2023; Patrick et al., 2021). Studies have observed an overlap in the ventromedial prefrontal cortex which plays a key role is valuation network of both effort and delay discounting, even though these decisional costs are processed in separate regions (Klein-Flügge et al., 2015; Lopez-Gamundi et al., 2021). This points to the mechanism which governs how an individual values his goals in context of effort and time required to achieve it and how its maps on to behavioural actions. However, even though delay and effort discounting have complimentary functions, they provide a structurally incomplete account of willpower failure. Real life goal-oriented conflicts do not present these costs in isolation; for example, someone resisting a dietary temptation must tolerate both effort of restraint in the present and the delay before the experience of health benefits. Hence, treating these costs as separable poses a methodological limitation as well as ecological inadequacy to study willpower failures.

The integration of delay and effort within a single valuation framework is both theoretically motivated and neurologically plausible yet remains methodologically challenging. Research on risky intertemporal choice has shown that delay and risk interact multiplicatively in shaping reward valuation (Vanderveldt et al., 2015; Wang et al., 2020), setting a precedent for multi-cost discounting frameworks. However, extending this logic to delay and effort is complicated by a fundamental parametric incompatibility as found in empirical literature. Delay discounting is best described by hyperbolic functions, whereas effort discounting follows concave functions for physical effort and hyperbolic or convex functions for cognitive effort (Bialaszek et al., 2017; T. T.-J. Chong et al., 2018). Despite this functional divergence at the level of discounting curves, neuroimaging evidence shows that delay and effort are not independently valued in a choice conflict. Functional convergence at the striatum and vmPFC suggests that both costs are integrated into a common subjective value signal providing the neural basis for a combined discounting mechanism (Massar et al., 2015; Prévost et al., 2010a; Suzuki et al., 2020). We propose that willpower failures can be captured within this dual cost integrated decision-making paradigm as it sheds light on the decisional dynamics of a goal-directed self-regulatory conflict.

Effort-Based Delay Discounting as a mechanism for Willpower

We developed a novel Effort-Based Delay Discounting paradigm by modifying the existing COG-ED task (Westbrook et al., 2013a) to incorporate temporal delays alongside cognitive effort demands in the choice

structure. Participants repeatedly chose between a low-effort task resulting in a smaller immediate reward and a high-effort task yielding a larger but delayed reward. This choice architecture mirrors the structure of a real-life willpower conflict, where the easier immediate option is the temptation and making goal-oriented choices requires tolerance of both effort and delay costs. The repetitive trial structure of this paradigm enables capturing the resolve aspect of willpower via intertemporal bargaining as described by Ainslie (2013, 2020), where each present decision functions as evidence for future decision patterns reflecting sustained self-regulation of goals. The mechanistic logic of this design is grounded in Temporal Motivation Theory (Steel, 2010), which suggests that subjective value declines more steeply when pursuing future goals that require a sustained effort across delays. This pattern is consistent with the motivational lapses seen in procrastination and academic performance (Janson et al., 2024; Steel, 2010). Complementing this effect, Temporal Self-regulation Theory (P. A. Hall & Fong, 2007) highlights the conflict between an individual's behavioural prepotency towards effortful demands and their executive capacity determines self-regulatory success. In context of effort-based delay discounting, it explains that different levels of regulatory success depend on how demanding the effortful option is relative to their available executive resources at that moment. Here effort sensitivity is not a fixed attribute but acts as a dynamic modifier navigating willpower conflicts among individuals. This choice architecture simultaneously engages the systems proposed in Bechara's (2005;2007) neurocognitive mechanism of willpower. The immediate effort cost overloads the impulsive system's aversion signal while simultaneously activating the reflective system to sustain representation of the delayed reward, making effort-based delay discounting a structurally complete operationalization of the willpower conflict.

To address the parametric incompatibility of delay and effort discounting functions, we have quantified effort-based delay discounting using a model-free composite measure, Volume Under Surface (VUS). This is an extension of the point-based area under curve (AUC) using numerical integration methods, which are very commonly used in unidimensional delay and effort discounting studies in the absence of prior estimates of a mechanistic process of discounting (Myerson et al., 2001; Westbrook et al., 2013b). It is computed using two-dimensional numerical integration across each participant's full discounting surface. A lower VUS reflect steeper combined discounting exposing a higher vulnerability to willpower failure under joint cost demands.

Current Study

In the present study, we aim to test the combined effects of effort and delay on the subjective value of a monetary reward. We hypothesize a multiplicative influence of these two computational costs in the valuation of

the reward during decision making. Moreover, we also aim to explore the interaction fingerprint of how delay and effort influence effort-based delay discounting. Secondly, we derive a composite behavioural measure Volume Under Surface (VUS) to describe the individual differences in integrated discounting across effort and delay, along with AUC measures for delay and effort across cost dimensions to represent independent cost sensitivities. Discriminant validity of VUS is evaluated against trait variables such as delay gratification, need for cognition, action control, trait willpower and physical effort. Finally, this study seeks to position VUS as a quantifiable metric of willpower by conceptualizing it as an emergent property of integrated value-based decision making, within the broader landscape of inhibitory control research. We propose that this reconceptualization is likely to reflect a distinct process of exertion and failure of willpower, which is not captured by traditional self-report measures.

Methods

Participants

62 healthy adult participants (45.2 % females) between the ages of 18 and 36 (mean age: 21.8, SD: 4.51), were recruited for this study from the {anonymized for peer review}. The participants were proficient in English language, had no history of any psychiatric disorders and were currently not on any psychotropic medication. A simulation-based power analysis was conducted to estimate the sample size required to reliably detect the interaction effect. The study was conducted in accordance with the guidelines of the ethical research committee, along with the approval from the Ethics Committee at {anonymized for peer review}. All participants provided their written informed consent and were compensated with incentives for participation. Among all participants, 37 were students recruited from undergraduate Psychology course and credit for their participation. All participants were monetarily compensated with twenty percent of their selected reward amount from one of their randomly selected trials from the decision-making phase. Rewards were delivered either immediately or after a delay, depending on their chosen task.

Measures

Delay Gratification

This study used the 35-item Delay Gratification Inventory (Hoerger et al. 2011) developed to assess the trait-level dispositions to forego the immediate experience of satisfaction for the sake of long-term benefits. Participants responded on a 5-point Likert scale ranging from *strongly disagree* (=1) to *strongly agree* (=5). After

scoring the items including 18 reverse-coded items, the mean score of the participant was calculated to denote their tendency to delay gratification. The internal consistency of the scale was satisfactory (M = 3.65, SD = 0.360; Cronbach's α = 0.80; McDonald's omega ω= 0.82).

Need for Cognition

The trait-level measure of the participant's tendency to seek and engage in effortful cognitive activities, was assessed by using a 6-item Need for Cognition Scale (NFC-6) which is a short version of the original NFC developed by Cacioppo and Petty (Lins de Holanda Coelho et al. 2020). The scale showed a satisfactory internal consistency (M = 3.86, SD = 0.64; Cronbach's α = 0.72; McDonald's omega ω= 0.74).

Action Control

This study assessed the individual differences between the participant's ability to plan, initiate and to execute goal-directed actions, using the 24 item, English version of Action Control Scale (ACS-24) originally developed by Kuhl, 1994. It has two sub-scales which measure, Action Orientation after Failure (AOF) and Action Orientation related to Prospective Decisions (AOD). Each sub-scale contains 12 items describing a scenario. Participants were given two alternatives as responses to each item (A or B), one of which is indicative of action orientation and the other of state orientation. The action control score was calculated based on the number of action-oriented answers given by the participant, and the sub-scales were scored separately as each dimension dealt with a separate behavioural aspect of action orientation. Internal consistency of the scale was satisfactory (M = 0.43, SD = 0.236; McDonald's omega ω= 0.86). The overall Cronbach's α was 0.94, while Cronbach's α for AOF and AOD were 0.80 and 0.78 respectively.

Physical Effort

Physical Effort Scale (PES-8), an 8-item bidimensional scale was used to assess the individual differences in the participant's approach and avoidance tendencies toward physical effort (Cheval et al., 2024). The scale consisted of 4 items in each dimension: Approach of PE and Avoidance of PE. Participants indicated their level of agreement with each item on a 5-point Likert scale. The internal consistency of the scale was very good (M = 2.69, SD = 0.957; Cronbach's α = 0.94; McDonald's omega ω= 0.94).

Trait Willpower

To validate the experimental task with a congruent measure of willpower as a personality trait, this study used the 38 item English version of the Willpower Heptet Scale (WHS-38) (Okan, 2025). This scale has 7 sub-

dimensions related to willpower: determination, reasoning, responsibility, consistency, choice, decision-making and self-control. The total score represented the overall level of willpower. Participants were instructed to answer to the items by mentally adding the phrase "*In important situations in my life….*" before responding to a 7-point Likert scale ranging from (1) Never to (7) Always. The scale showed good reliability estimates (M = 5.20, SD = 0.699; Cronbach's α = 0.93; McDonald's omega ω= 0.94).

Task Design and Procedure

In this study, we adapted the COG-ED task and modified its structure to assess a novel measure of combined discounting of monetary reward under the influence of increased neural costs associated with cognitive effort and temporal delay. Following the same task structure developed by Westbrook et al., 2013, we systematically varied cognitive load levels using n-back tasks (2-back, 3-back and 4-back) along with the novel addition of 6 levels of delays (1, 7, 14, 30, 90 and 180 days). We adopted a 3 (cognitive effort) x 6 (delays) factorial design resulting in 18 conditions in which the low effort immediate reward was titrated across 8 trials per block to calculate the subjective value of the delayed effortful reward of INR 1000. If the participant chose the larger reward in any trial, then the smaller reward was increased, and if the participant chose the smaller immediate offer, then the smaller reward was decreased. For every choice in each block, the adjustment was made by halving the previous adjustments. This resulted in 144 decision trials (3 higher levels of n-back tasks across 6 levels of delays for 8 trials each), and 18 indifference points per participant. The task was designed in PsychoPy software (Peirce et al., 2019), where the task conditions were counterbalanced to avoid order effects (M. Eisenberg & Barry, 1988). Since the experiment was divided into 3 phases, each phase was programmed into separate experimental sessions using PsychoPy. Python codes used in task components were developed with assistance from Claude (Anthropic, claude.ai, 2025). All code was reviewed and validated by the authors prior to use.

Participants completed the experiment session in 3 phases namely, the experience phase, the decision-making phase and the choice implementation phase. In the first phase, participants experienced 4 levels of n-back tests which is a widely used measure of working memory (Jaeggi et al., 2010) as well as the crucial measure of individual differences in cognitive effort demands within the Cognitive Effort Discounting paradigm. Participants completed a standardized instruction and practice protocol for every level of the n-back task. For each level (1-4), the n-back task included 30 items (consonants, 7 targets and 23 non-targets). The stimuli were presented at an inter-item interval of 3.5 seconds, where the participants had 1.5 seconds to respond by pressing a button after which the item was replaced with a fixation cross. The practice session for each-level of n-back task included 12

presentations including 3 target and 9 non-target letters, where participants were given feedback on their accuracy. After the practice session, they completed two runs of each level of n-back task (60 items including 14 targets and 46 non-targets) followed by completion of the NTLX to assesses subjective task load as a manipulation check.

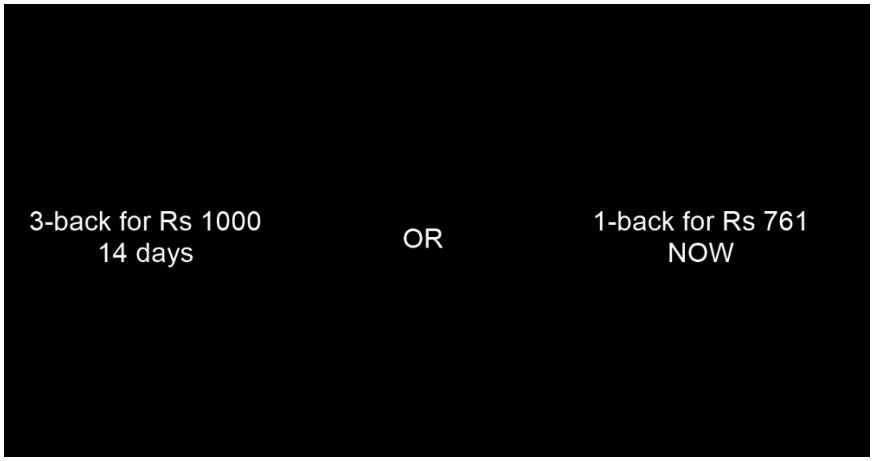


Fig. 1: *Example of forced choice decision trial*

Post the n-back experience phase, the participants made 144 forced-choice decisions (see Figure 1) involving potentially incentivized choice of either completing a (1-back, low effort task) for a smaller reward available immediately or completing a high effort task (2-back, 3-back or 4-back test) for a higher fixed reward of Rs 1000 available after a certain number of days (1, 7,14,30,90 and 180 days). Participants were also instructed that one of their decisions made in phase 2 will be randomly selected from their chosen options for phase 3, where they will have to do the n-back task chosen for 4 runs and will be rewarded accordingly. They were told that their reward was not contingent on performance of the n-back task, but on maintaining the same level of effort throughout the duration of the task as in first phase. Participants who completed a 1-back task were paid their reward amount immediately and participants who completed n-back levels of 2, 3 and 4 were paid their reward amount after the selected duration of the random choice. At the end of the experiment session participants provided their e-wallet information, and the date of compensation was scheduled in the google calendar for their assurance. Subsequently, the participants completed a battery of self-report questionnaires administered via a Google form survey. These measures were collected after the experimental session to avoid demand characteristics or priming effects on decision-making during the task. The questionnaire battery included trait and state variables relevant to effortful and intertemporal decision-making and its correlates to examine the individual differences in effort-based delay discounting profiles of each participant.

Data Analysis

Preprocessing of data included extraction of the reaction time for each decision trial for every participant and averaging it for further analysis. Moreover, performance in n-back task was quantified by estimating the d prime (d') scores for every effort level based on z-transformed hit rate minus z-transformed false alarms rate (Leathem et al., 2025). Subjective Value (SV) was estimated using a staircase titration procedure to obtain indifference points, where the SV represented the ratio of the indifference amount to the delayed effortful reward. To examine the trial-level effects of delay and cognitive effort on the reward valuation, we fitted two linear mixed models (LMMs) using the *GAMLj* module in JAMOVI ver. 2.7.6 (https://www.jamovi.org). Linear Mixed Effects Modelling approach is becoming increasingly popular for its statistical rigour in analysing manipulation effects in repeated measures design and well as nested data structure because it models individual trial-level observations instead of averaging scores which retains more information and data points making it more suitable for smaller sample studies (Nakagawa & Schielzeth, 2013; Wiley & Rapp, 2019). Model selection followed a theoretically grounded and sequential building strategy. An unconditional model was first estimated to establish baseline ICC, to isolate between group clustering in the data due to individual differences. This motivated inclusion of random effects in the baseline model. Baseline model (M0) included the fixed effects of delay, effort, and their interaction along with random intercepts. Consistent with theoretical accounts of individual differences in effort sensitivity, random slopes for effort were added into the baseline model, yielding M1. We also considered adding random slopes for delay, but it was not retained in the random effect structure of any further model due to two specific reasons. First, adding five delay contrasts as random slopes would require estimating a complex 6x6 covariance matrix with 15 correlation parameters, from 62 participants. This made the model over-parameterized and could lead to potential convergence issues. Secondly, this was empirically validated when including random slopes for delay generated singular fit warnings with some variance components collapsing to zero, making the estimates unreliable (See results in the Supplementary File). Thus, we settled on two candidate models to report. The first model fitted tested the fixed effects of delay, effort, and their interaction along with random intercepts and random slopes for effort across participants to accounts for individual differences.

$$M1 = SV\sim 1+ Delay + Effort + Delay \times Effort + (1 + Effort \mid Subject)$$

The second model extended this specification by including the task-performance covariates such as average Reaction time (mRT) for each combination of delay and effort (denoted by a) and the d prime at each load level (denoted by i) of n-back task. Individual-level mean centring was applied to both covariates to isolate within group condition level fluctuations in performance from stable between group differences in speed and accuracy,

while yielding an accurate evaluation of whether trial-level performance confounded the reward valuation (Enders & Tofighi, 2007).

$$M2 = SV\sim 1 + Delay + Effort + mRT_a + d'_i + Delay \times Effort + (1 + Effort \mid Subject)$$

Model estimates were obtained using restricted maximum likelihood estimated, and fixed effects were estimated using Type III tests with Satterthwaite approximations of degrees of freedom. To further explore the interaction delay and effort, post-hoc analysis were conducted using estimated marginal means (EMMs). Pairwise comparisons and simple effects analysis were performed to delineate the pattern of the interaction effect which provided a more granular understanding of how integrated cost valuation influences choice impulsivity.

Additionally, a simulated power analysis was conducted using the simR package in R (Green & MacLeod, 2016). The data simulated was based on the fitted LMMs, where the interaction effect was evaluated using a Type III omnibus F-test with sum-to-zero contrasts and power was estimated as the number of times out of 500 simulations per condition, interaction effect was significant at $\alpha = 0.05$. Power was computed for the current sample size (N=62) as well as projected sample size (N= 75, 80, 90) by extending the model along the participant dimension. This technique confirmed the adequacy of our current sample size as the achieved power (0.98) to detect the hypothesized interaction effect (see Fig S2 in Supplementary file) given the observed variance estimates reflected true population parameter was more than 0.80, it is considered acceptable (Kumle, 2024).

Computation of Volume Under Surface (VUS)

The composite measure of effort-based delay discounting, Volume Under Surface (VUS) was computed from nested trial-level choice data using a two-dimensional integration approach using the R package pracma in R studio (Borchers, 2011). This metric was inspired from the research to analyse time series data, where AUC measures were extended to incorporate analysis of more than one choice parameter in a three dimensional space (Paparrizos et al., 2022). Delay, effort and SV were all normalized to ensure that all variables were bounded between 0 and 1 for equal contribution to representation of the 3-D surface. Next, for each participant, a two-dimensional matrix of normalized SV values was constructed across exclusive combinations of normalized delay and effort. This matrix conceptually characterized the surface where each 18 grid points correspond to a unique pair of delay and effort. The construction of this surface follows the principle analogous to bilinear interpolation where the values organised on a 2-D grid (Dnorm and Enorm) and the surface between the SVs is implicitly approximated as piecewise planar (Mastyło, 2013). This enables the valuation surface to be treated as a continuous function over the two dimensions. VUS was then calculated using a nested application of the trapezoidal rule

which is commonly used in calculating AUC for discounting studies (Myerson et al. 2001). The nested integration structure involved, integration function along the delay dimension for each level of effort (inner integration) followed by integration of these values across the effort dimension (outer integration). This can be formally expressed which in discrete form using the trapezoidal rule as:

$$VUS \approx \sum_{j} \left[\sum_{i} (d_{i+1} - d_i) \frac{SV_{i,j} + SV_{i+1,j}}{2} \right] (e_{j+1} - e_j)$$

Here, d represents the levels of delay and e represents the effort level; *i* and *j* indexes the ordinal levels of delay and effort respectively such that $SV_{i,j}$ represents the subjective value of the reward at each delay x effort block. This two-step procedure yields the total VUS for each subject. It provides a single scalar behavioural index of the extent to which the reward is devalued subjectively across increasing delay and effort costs. Like AUC measures, here also lower VUS values indicate steeper combined discounting.

Finally, to explore the association of the VUS with theoretically related constructs we conducted a Bayesian Correlation Analysis which is consistent with methodological recommendation in prior studies especially for small sample size like ours (McNeish, 2016a). The analysis was performed to find evidence for discriminant and convergent validity of VUS as a proxy measure of willpower with AUC measures of independent delay and effort discounting and self-reported trait variables. The development of R codes for the simulated power analysis, computation of AUC and VUS as well as plotting of figures was assisted by Claude (Anthropic, claude.ai, 2025). All codes were verified and assessed prior to use.

Results

Preliminary Checks: N-back Performance and Manipulation Check

Descriptive statistics for d' across all n-back levels decreased monotonically across load levels as presented in Table 1. To verify the effect cognitive load levels in the effort manipulation, a one-way repeated measures ANOVA was conducted on the d' scores across the four n-back levels. Mauchly's test indicated that the assumption of sphericity was violated, W= 0.79, p = 0.015, and therefore the df were corrected using the Greenhouse-Geisser estimate (ε = 0.86) (Greenhouse & Geisser, 1959). The main effect of n-back level was significant on performance (d'), F (2.57, 156.66) = 163.00, p<.001, partial $\eta^2 = 0.728$ (see Table 2). Bonferroni-corrected post-hoc comparisons (see supplementary file) confirmed that all pairwise differences between n-back levels were statistically significant at 0.001 level, including the intra-level comparisons (2-back vs 3-back: MDiff

= 0.827, SE = 0.118, t(61) = 6.99; 3-back vs 4-back: MDiff = 0.752, SE = 0.105, t(61) = 7.61). This confirmed that each increment in cognitive load produces a reliable and stepwise decline in working memory performance. Subjective task load assessed via the NTLX showed a similar monotonic increase in perceived difficulty across n-back level (2-back: M = 45.20, SD = 9.78; 3-back: M = 60.86, SD = 10.12; 4-back: M = 65.82, SD = 11.51), providing convergent validation of effort manipulation of each participant.

Table 1

Descriptive Statistics for N-back Task Performance, Response Times, and Discounting Metrics

Variable	M	SD
N-back Task Performance (d')		
2-back	3.42	0.642
3-back	2.59	0.943
4-back	1.84	0.726
NASA Task Load Index (NTLX)		
2-back	45.2	9.78
3-back	60.86	10.12
4-back	65.82	11.51
Mean RT per Condition (s)		
2-back × 1 day	3.15	1.78
2-back × 7 days	2.86	1.42
2-back × 14 days	3.17	1.74
2-back × 30 days	3.25	1.32
2-back × 90 days	3.71	2.96
2-back × 180 days	3.11	1.93
3-back × 1 day	3.4	2.07
3-back × 7 days	3.17	1.94
3-back × 14 days	2.7	1.27
3-back × 30 days	3.31	1.74
3-back × 90 days	3.42	1.89
3-back × 180 days	2.92	1.31
4-back × 1 day	3.29	2.34
4-back × 7 days	2.8	1.25
4-back × 14 days	3.2	2.01
4-back × 30 days	3.12	1.63
4-back × 90 days	3.28	1.82
4-back × 180 days	3.06	1.72
Discounting Metrics		
Volume Under Surface (VUS)	0.33	0.22
AUC_{Delay}	0.32	0.22
AUC_{Effort}	0.58	0.17

Table 2

Repeated measures ANOVA summary of N-back level

	SS	df	Mean Square	F	p	η^2	η^2p
N-back	158.8	2.57	61.82	163	<.001	0.575	0.728
Residual	59.3	156.6	0.37				

Table 3

Linear Mixed Models of Subjective Value (M1: Primary Model; M2: Covariate Adjusted Model)

	M1				M2			
Predictor Terms	**F**	**df**	**df(res)**	**p**	**F**	**df**	**df (res)**	**p**
N = 18 conditions * 62 participant = 1116 observations								
Fixed Effects								
Delay	98.06	5	915	<.001	98.12	5	914.2	<.001
Effort	49.26	2	61	<.001	28.2	2	75.2	<.001
Delay × Effort	2.78	10	915	0.002	2.7	10	914.1	0.003
mRT (person-mean centred)					2.6	1	982.9	0.107
d′ (person-mean centred)					0.31	1	85.3	0.574
Model Fit Indices								
R^2 conditional	0.702				0.703			
R^2 marginal	0.242				0.243			
AIC	-187.2				-170.5			
BIC	-61.8				-35			
Log-likelihood	118.6				112.2			

Effects of Effort and Delay on the Subjective Value of Reward

To examine the effects of cognitive effort and delay on reward valuation, a linear mixed model was fitted with the subjective value (SV) as the outcome variable. The primary fixed effects model (M1) demonstrated an excellent fit, with a conditional R^2 of 0.702, indicating that fixed and random effects together explained 70.2 percent of total variance in SV. The marginal R^2 was 0.241, reflecting the variance explained by the fixed effects alone (see Table 3). This gap between the conditional and marginal R^2 explains that stable individual differences in effort sensitivity, captured by the random slope structure (Nakagawa & Schielzeth, 2013). Omnibus test revealed that fixed effects of Delay ($F(5, 915.0) = 98.06$, $p<.001$) and Effort ($F(2, 61.0) = 49.26$, $p<.001$) were

highly significant in reduction of SV. Post hoc analysis of Estimated Marginal Means illustrated the extent of value degradation across the cost surface (see Table 4).

Table 4

Estimated Marginal Means of Subjective Value Across all conditions

Effort	Delay (days)	EMM	df	SE
2-back	1	0.79	138	0.0363
	7	0.66	138	0.0363
	14	0.56	138	0.0363
	30	0.50	138	0.0363
	90	0.39	138	0.0363
	180	0.32	138	0.0363
3-back	1	0.62	123	0.0386
	7	0.47	123	0.0386
	14	0.45	123	0.0386
	30	0.38	123	0.0386
	90	0.32	123	0.0386
	180	0.27	123	0.0386
4-back	1	0.42	141	0.0359
	7	0.34	141	0.0359
	14	0.30	141	0.0359
	30	0.22	141	0.0359
	90	0.19	141	0.0359
	180	0.15	141	0.0359

Table 5

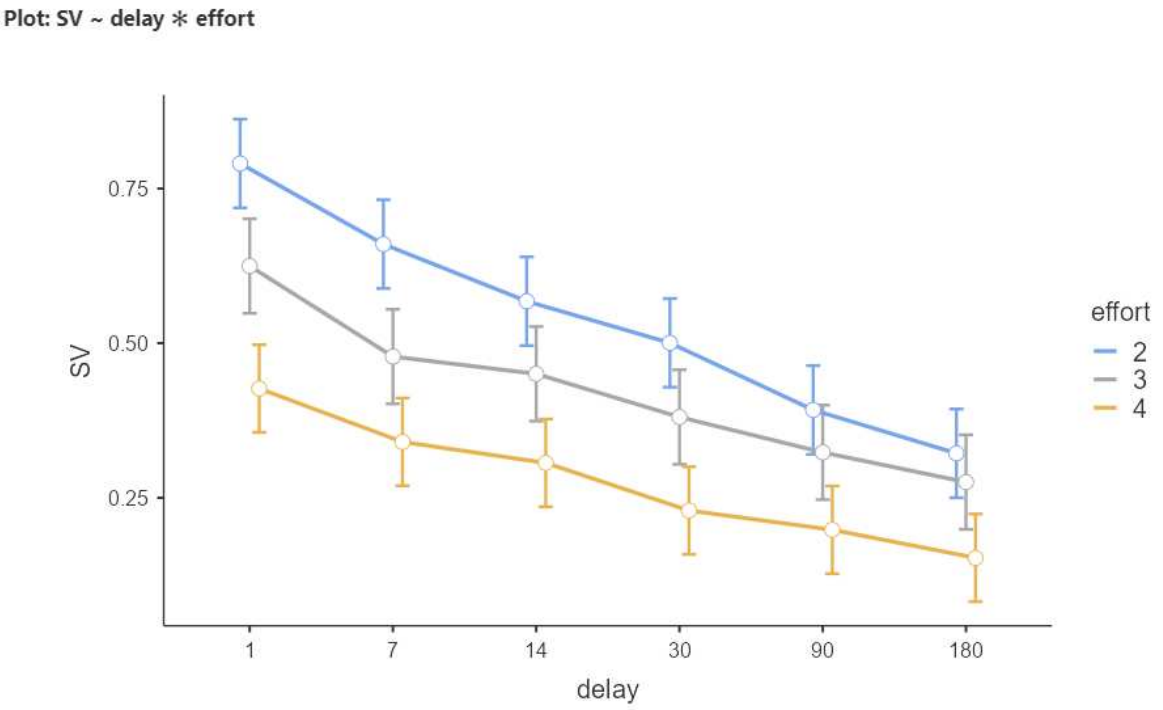
Simple Effects of Delay on Subjective Value at Each Level of Effort

Moderator				95% CI				
effort	Effect	Estimate	SE	Lower	Upper	df	t	p
2-back	7 − 1	-0.13	0.032	-0.19	-0.06	915	-3.98	<.001
	14 − 1	-0.22	0.032	-0.28	-0.15	915	-6.79	<.001
	30 − 1	-0.29	0.032	-0.35	-0.22	915	-8.85	<.001
	90 − 1	-0.39	0.032	-0.46	-0.33	915	-12.12	<.001
	180 − 1	-0.46	0.032	-0.53	-0.4	915	-14.3	<.001
3-back	7 − 1	-0.14	0.032	-0.21	-0.08	915	-4.47	<.001
	14 − 1	-0.17	0.032	-0.23	-0.11	915	-5.32	<.001
	30 − 1	-0.24	0.032	-0.3	-0.17	915	-7.45	<.001
	90 − 1	-0.3	0.032	-0.36	-0.23	915	-9.2	<.001

	180 − 1	-0.34	0.032	-0.41	-0.28	915	-10.66	<.001
4-back	7 − 1	-0.08	0.032	-0.15	-0.02	915	-2.63	0.009
	14 − 1	-0.12	0.032	-0.18	-0.05	915	-3.67	<.001
	30 − 1	-0.19	0.032	-0.26	-0.13	915	-6.02	<.001
	90 − 1	-0.22	0.032	-0.29	-0.16	915	-6.97	<.001
	180 − 1	-0.27	0.032	-0.33	-0.2	915	-8.35	<.001

Beyond the independent additive effects of delay and cognitive effort on SV, a multiplicative interaction term was found to be statistically significant, $F(10, 915.0) = 2.78$, $p = .002$. To characterize the interaction pattern, simple effects of delay were examined at each level of cognitive effort as presented in Table 5. At the lowest effort level (2-back), delay discounting gradient is the steepest, with SV declining by 0.469 units from 1 day to 180 days delay conditions (95% CI [-0.533, -0.404], $t(9150 = 14.30$, $p < 0.001$). This discounting gradient is attenuated with successively higher effort levels; at 3-back and 4-back, SV declines by 0.350 and 0.274 units respectively. This reduction represents an overall attenuation of almost 42 percent of delay discounting effect from lowest to highest effort level. Complementarily, fixed effects of effort across delay levels exhibited a symmetric attenuation of effort discounting gradient. Effort discounting was steepest at the shortest delay 1 day where the SV declined by 0.364 units and progressively compressed at longer delays, reducing up to 0.169 units at 180 days. This pattern is visually expressed in Fig.2 which shows the convergence of delay and effort lines across increasing effort and delay levels.

Fig. 2: *Interaction Effect of delay and effort on SV*



The covariate adjusted model (M2) retained the same random effects structure as M1. Model fit was comparable to M1, with a conditional R^2 of 0.703 and a marginal R^2 of 0.243. Neither of the performance covariates reached statistical significance; mRT, F(1,982.9) = 2.604, p = 0.107 and d', F(1,8503) = 0.319, p = 0.574 (see Table 3). Comparison of model fit indices between M1 and M2 indicated the addition of covariates provided negligible incremental explanatory power (M1: AIC/BIC = -187.2/-61.8; M2: AIC/BIC = -170.5/-35.0). Thus, M1 retained superior parsimony despite the marginal increase in conditional R^2 from 0.702 to 0.703. The non-significance of both covariates confirms that within person differences did not confound the valuation of the delayed and effortful reward. Interestingly, the effort x delay interaction replicated with almost identical magnitude after covariate adjustment, F(10,914.1) = 2.709, p = .003, further confirming the proposed hypothesis.

Random Effects Structure

The intraclass correlation coefficient from M1 indicated 57.0 percentage of total variance (ICC = 0.570) in SV was attributed to stable individual difference. Examination of random slope variances revealed that individual variability was greater for the highest effort contrast (0.033) than for the lower effort contrast (0.009). A moderate correlation was observed between effort1 (2-back vs 3-back) and effort2 (3-back vs 4-back) random slopes (r = 0.59). Mirroring this outcome, the random effects structure remained stable in M2 (ICC = 0.571) and identical random slope variances (see Supplementary Table S2).

Effort-based Delay Discounting: VUS and AUC Descriptives

Individual differences in how people devalue a delayed and effortful reward was operationalized using the Volume Under Surface (VUS), computed from each participant's 18 indifference points across the full effort x delay surface. This composite behavioural metric showed substantial variability in the sample (M= 0.33, SD = 0.22, range =0.002 to 0.920), spanning almost across the full range of the normalised scale and indicating that participants had distinct profiles of effort-based delay discounting. The sample mean of 0.33 further suggests that on average, participants retained approximately one third of the reward's full subjective value across the surface, reflecting a general tendency towards steep discounting in the sample. Further, to contextualize the integrated discounting profile captured by VUS, marginal AUC measures (AUC_{Delay}: M= 0.32, SD = 0.22 and AUC_{Effort}: M= 0.58, SD = 0.17) were derived from the same data as unidimensional summaries of each independent cost dimension (see Table 1). At the group level, AUC plots of delay and effort discounting followed a hyperbolic and concave curve (see Fig S1a and S1b in Supplementary File), verifying the parametric incompatibility of these cost dimensions and empirically justifying the model free VUS approach adopted in this study.

Fig. 3a: AUC of delay across effort levels

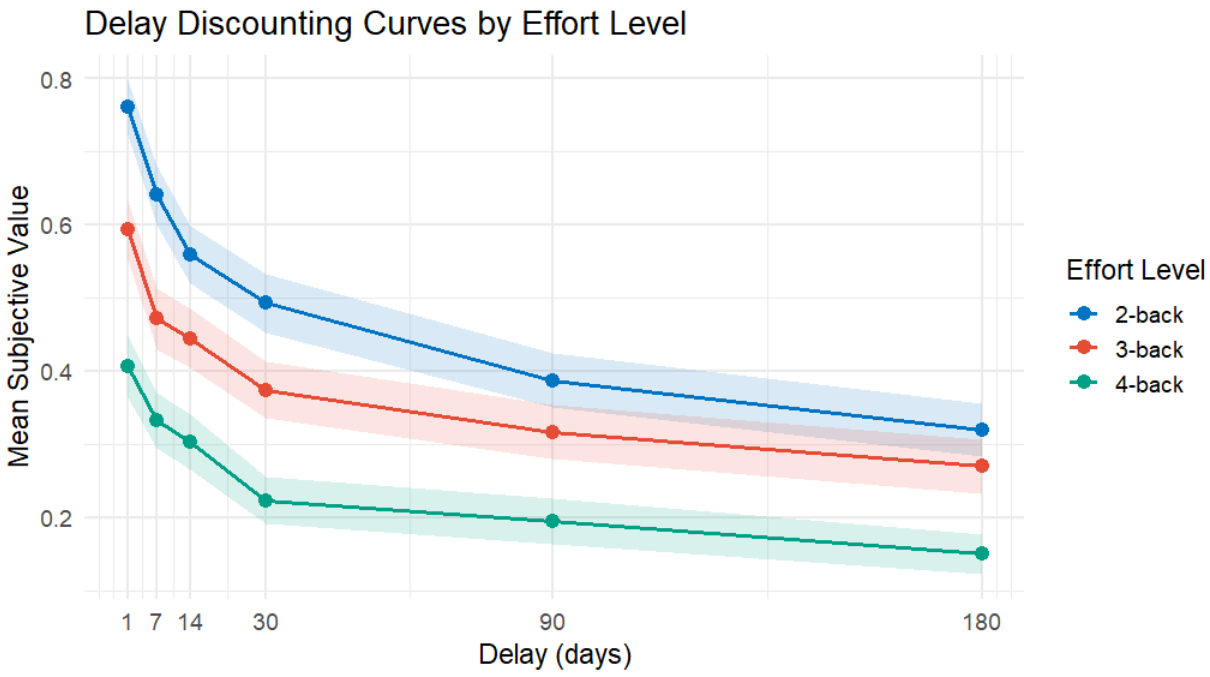
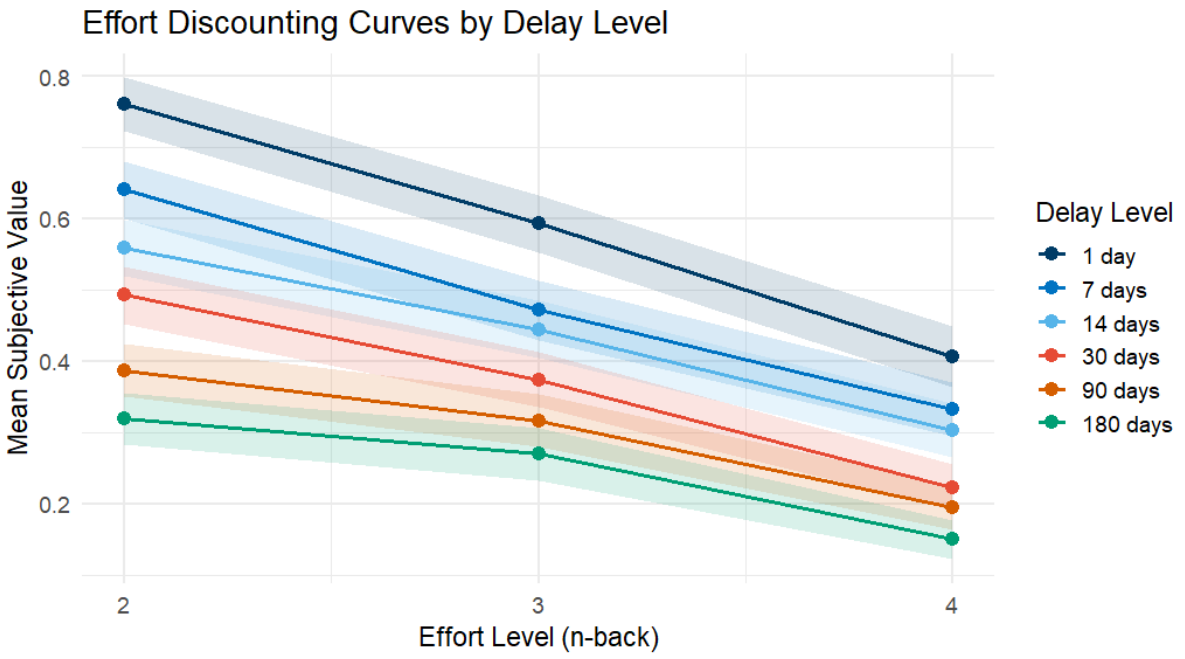


Fig. 3b: AUC of effort level across delays



Further to illuminate the nuance of the interaction between the cost dimensions, AUC of delay was computed separately at each effort level as was AUC of effort at each level of delay to depict 2D slices of combined discounting. As shown in Figure 3a, delay discounting curves at each effort level retained a characteristic steep initial devaluation that flattened across longer delays, exhibiting progressive decline and convergence at higher effort loads. AUC_{Delay} decreased systematically from 2-back (M= 0.42, SD = 0.25), through 3-back (M= 0.33, SD = 0.26) to 4-back (M= 0.20, SD = 0.22). Correspondingly, effort discounting curves at each delay level showed a consistent declining pattern of six converging curves cross increasing effort levels, shown in Figure 3b. AUC_{Effort} decreased from the shortest delay (1 day: M = 0.73, SD = 0.19) to the longest (180 days: M = 0.45, SD = 0.18), reflecting the compression of effort sensitivity under increasing temporal demands. Together, these 2D slices directly mirror the interaction and motivate VUS as the appropriate descriptive measure to capture full effort-based delay discounting surface without collapsing across either cost dimension or imposing parametric assumptions on their functional relationship. Individual and group level discounting surfaces as present in Figure 4 and Figure 5. At the sample level, the group surface reflects a trend towards steeper discounting, which is consistent with the mean VUS of 0.33. The contrast between individual surfaces indicates meaningfully distinct discounting profiles captured effectively by VUS (Fig 5a and 5b). It clearly shows that a steep discounter's surface reflects an almost full erosion of reward value under increasing costs which means that the motivational pull of the effortful delayed reward was overwhelming for the participant due to the joint influence of delay and effort demands. Conversely, the shallow discounter's surface shows a substantial retention of the reward value across

the cost space, suggesting that the participant's tolerance to increasing delay and effort costs implies a tendency of sustaining goal-directed valuation.

Fig. 4: *Volume Under Surface of the Group*

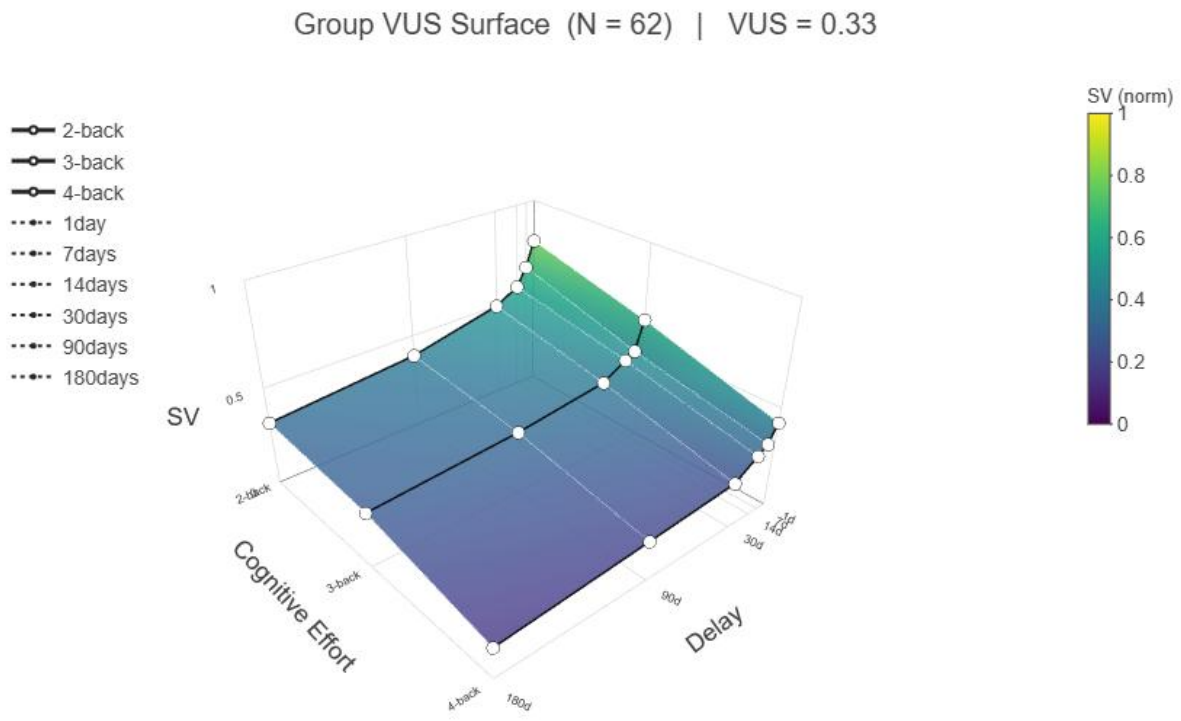


Fig. 5: *Individual Differences in Effort-based Delay Discounting as captured by VUS*

Note: VUS surface of subject 27 on the left indicates a steep Effort-based Delay Discounting profile characterized by the erosion of SV across both the cost dimensions; VUS surface of subject 35 on the right describes a shallow Effort-based Delay Discounting profile, where the SV has retained its value across all the cost combinations, without drastically collapsing at high effort or delay levels.

Individual VUS Discounting Surfaces

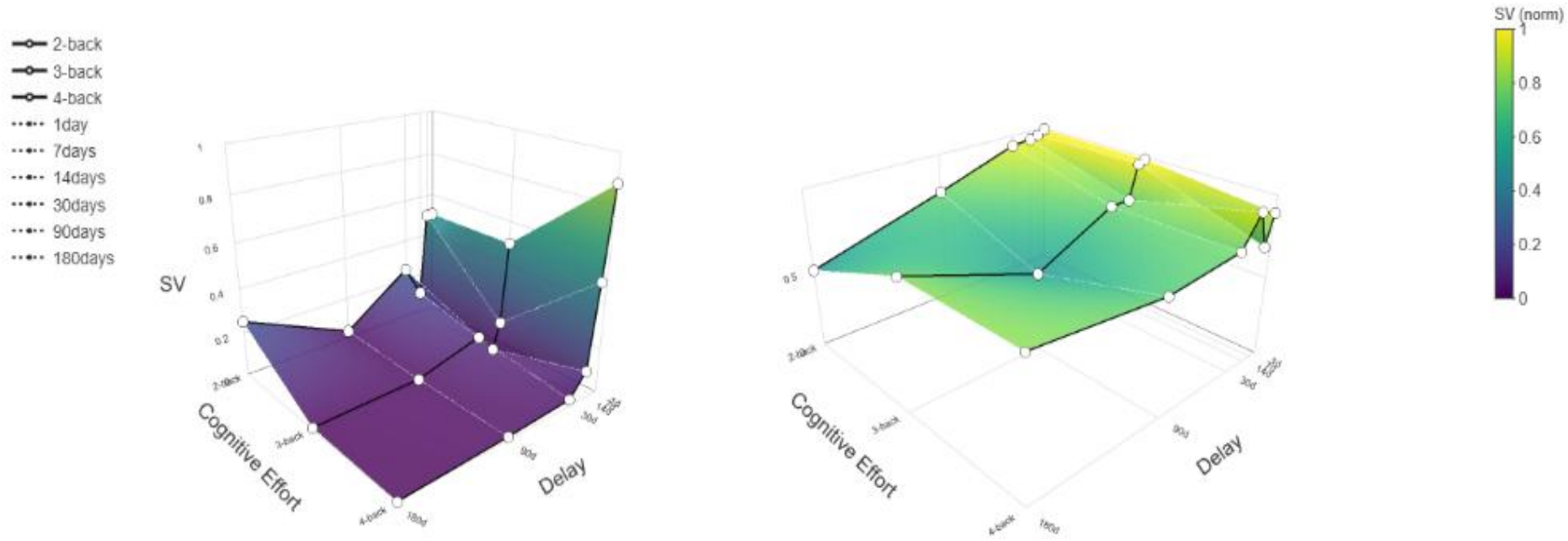


Table 6

Bayesian Correlations Between Volume Under Surface (VUS) and Self-Report Measures of Willpower-Related Traits

			95% CrI		
Variable	*r*	**BF_{10}**	**Lower**	**Upper**	**Interpretation**
Trait Willpower	-0.01	0.16	-0.26	0.22	Moderate evidence for null H0
Delay Gratification	-0.02	0.16	-0.26	0.22	Moderate evidence for null H0
Need for Cognition	0.17	0.38	-0.07	0.39	Moderate evidence for null H0
Action Orientation after Failure	0.1	0.21	-0.14	0.33	Moderate evidence for null H0
Action Orientation towards Decision	-0.01	0.16	-0.27	0.21	Moderate evidence for null H0
Physical Effort	0.28	1.81	0.03	0.48	Anecdotal evidence for alternative H1

Preliminary Validity of VUS: Bayesian Correlation Analysis

All Bayes Factors were reported as BF_{10} under a default Jeffery's prior as presented in Table 6 (Wetzels & Wagenmakers, 2012). VUS showed near-zero correlations with all trait measures included in the battery which included trait Willpower (r = 0.018, BF_{10} = 0.160), Delay Gratification (r = 0.024, BF_{10} = 0.161), Overall Action Control (r = 0.038, BF_{10} = 0.165), Need for Cognition (r = 0.173, BF_{10} = 0.382), Decisional Action Orientation (r = 0.036, BF_{10} = 0.165) and Actional Orientation after Failure (r = 0.104, BF_{10} = 0.217). BF_{10} values consistently fell below 0.33 which denote moderate evidence in favour of the null hypothesis on Jefferey's scale (Ly et al., 2020). The sole directional signal emerged between VUS and trait level Physical Effort Sensitivity (r = 0.284, BF_{10} = 1.812), which reached significance in a conventional frequentist analysis (p = 0.026). However, the Bayesian evidence yielded was anecdotal, which means that it falls within uninformative range on Jeffery's scale.

DISCUSSION

The present study aimed to examine whether the dual influence of cognitive effort and temporal demands erode the value of a reward through independent mechanisms or through a mutual interaction. This distinction provides potential implications in explaining willpower failures in goal directed pursuits. Using a novel effort-based delay discounting paradigm with real monetary incentives, the findings of our study demonstrate that cognitive load and prospective delay each independently reduce subjective value, but critically their joint influence is not additive. The two cost dimensions were found to interact such that increasing cognitive effort systematically attenuates the gradient with which delay erodes value, compressing the function of delay discounting under high effort demands. Simple effects analysis confirmed this mutually constraining interaction structure which means that elevated cost demand of one cost attenuates the discriminating influence of the other

cost on reward valuation. The interaction effect survived even after adjusting performance related confounds in the task, further supporting our claims. This is consistent with a shared valuation bottleneck denoted by neural networks, producing a diminishing marginal devaluation rather than compounding costs (Botvinick et al., 2009; Prévost et al., 2010b). A high ICC of 0.57 indicated individual differences in baseline effort sensitivity which translates to the fact that the hardest effort level is where the differences in cognitive performance and effort sensitivity are most consequential for reward valuation. Correlation analysis using Bayesian methods indicated a discriminant validity for VUS which is theoretical consistent with the prior studies which have highlighted the dissociation between self-report measures of trait-level self-regulation and behavioural measures of decision-making (Barnhart & Buelow, 2017; I. W. Eisenberg et al., 2019; Enkavi et al., 2019). In summary, our findings illuminate evidence for understanding willpower failures as an emergent property of a decision-making process where multiple competing cost dimensions are dynamically integrated in the valuation of future outcomes which influence present actions.

Joint Influence of Effort and Delay in Effort-based Delay Discounting

The core empirical finding of our study is the significant interaction of delay and cognitive effort in determining the subjective value of a delayed and effortful reward. This interaction effect was robust to within-person confounds such as reaction time and cognitive performance. Previous studies have found critical inconsistencies between how delay and effort demands influence reward devaluation, where dissociable influences were found between discounting as a function of delay and physical effort (Klein-Flügge et al., 2015) while correlation was found in discounting as a function of delay and cognitive effort (Westbrook et al., 2013b). This suggests a knowledge gap in assessing the devaluation of reward under the combined influence of delay and effort where the nature of discounting is ambiguous among competing costs. Our finding addresses this ambiguity by shedding more light on the nature of this cost integration in valuation process, where we found that increasing cognitive effort demands progressively compressed the delay discounting gradient by almost 42 percent from the lowest to highest effort level. This indicates that higher cognitive demand did not merely promote uniform reductions in valuation but selectively reduced the decision weight assigned to temporal delay in discounting of the reward. This finding supports and adds nuance to the unified valuation network of temporal and orbitofrontal regions of the brain which encode both delayed as well as cognitively effortful rewards (Massar et al., 2015). Moreover, this pattern cannot be attributed to performance degradation under high cognitive load (Westbrook et al., 2013b) given that the interaction effect survived covariate adjustment for concurrent task accuracy, which means that it reflects a genuine shift in motivational decision making rather than a task induced confound. The

most parsimonious interpretation of this interaction invokes a principle of dynamic cost weighting. Our data shows that in under low cognitive effort demands, temporal delays influence the valuation process by producing steeper delay discounting gradient. As the effortfulness of the cognitive load increases, effort becomes a salient cost which competes with delay for decision weight, resulting in the diminishing relative influence of temporal demands in the devaluation of the reward. Conversely, at the lowest delay, effort carries the greater decision weight reflecting devaluation primarily due to a steeper effort discounting gradient. As the delays become longer, the temporal distance of the reward reasserts its decision weight as a cost driving the subjective devaluation. This pattern implies a context-dependent hierarchy of competing costs, in which neither effort nor delay consistently dominate the valuation process. Instead, each cost dimension alters the sensitivity to the other cost in a dynamic decision-making process. The joint dynamics of cognitive effort and delay costs observed here is consistent with empirical evidence from another paradigm which found that the temporal distance of cognitive effort demand reduced the magnitude of effort discounting and sensitivity to effort demands (Johnson & Most, 2023). Although their experimental design was different from ours, the structural logic shows analogous results, where they found increasing temporal distance attenuated the sensitivity to effort in their paradigm, very much like how we found that increasing cognitive effort demands attenuate the influence of delay sensitivity. This bidirectional modulation across different task paradigms and methodological heterogeneity strengthens the inference that effort and delay interact in valuation as mutually constraining costs rather than having separate additive influences. It is also worth noting that this claim is strengthened using real monetary incentives in our experimental task. Prior work in discounting literature applicable to both delay and effort cost has faced criticism for its inferential claims to explain behavioural tendencies using hypothetical rewards as they are known to yield less discriminating valuation functions along with the risk of not engaging the same valuation circuitry as real-life choices (Hinvest & Anderson, 2010; Miller et al., 2023; Ostaszewski et al., 2013). Accordingly, because participants received the monetary rewards of their choices, the present findings robustly capture the ecological structure of real-world valuation, where effortful and delayed rewards are pursued.

Preliminary Validity of VUS as a Descriptive measure of Willpower

Beyond the interaction effect, the present study investigated whether individual differences in the joint sensitivity to cognitive effort and delay could be meaningfully quantified. For this, we computed a model-free composite index of effort-based delay discounting, where Volume Under Surface (VUS) derived from the participant's estimated discounting surface descriptively exhibited wide variability in their discounting profiles ranging from almost flat surfaces showing low sensitivity to both costs to steeply eroded gradients reflecting high

sensitivity to delay and effort. This indicates meaningful individual differences and clarifies that the resulting discounting is not an artifact of the noise attributed to their baseline effort sensitivity. The individual differences in effort-based delay discounting profiles clearly suggest that VUS captures individual differences in how participants integrate these two costs in their valuation system.

The discriminant validity analysis provides preliminary support for considering VUS as a behavioural measure not reduced to related trait-level measures associated with impulsivity and effective self-regulation. Bayesian correlations indicated moderate evidence that VUS was unrelated to traits such as delay gratification, need for cognition, action control subdimensions as well as trait willpower. This is theoretically interesting because some of these traits have been closely associated with individual sensitivities to delay and effort separately in prior research. For instance, traits like delay gratification are used to predict self-control behaviours and is also closely related to traditional conceptualizations of willpower due to its established relationship with delay discounting which equates impulsive preferences with having a high sensitivity to temporal costs (Ainslie, 2020; Göllner et al., 2018; Yin et al., 2022b). Similarly, the trait of need for cognition has also been found to modulate the cognitive effort sensitivity which plays a vital role in motivated behaviours (Mækelæ et al., 2023; Scott et al., 2025; Zerna et al., 2023). Hence, the absence of any relationship with VUS highlights its unique feature of capturing the dynamic integration of delay and cognitive effort sensitivities where self-report indices which reflects personal beliefs about their trial-level dispositions do not map onto their actual behavioural signature of decision making. This dissociation of self-report trait indexes and behavioural discounting tasks are not uncommon in experimental psychology, where self-reported measures do not fully explain the behavioural counterpart (Enkavi & Poldrack, 2021; Lange & Eggert, 2015; Teglasi et al., 2017).

The convergent validity analysis revealed a directional positive association between VUS and trait-level approach or avoidance to physical effort which reflects the participant's sensitivity to physical effort. However, Bayesian evidence for this association was ambiguous which neither confirmed nor refuted the role of physical effort sensitivity in willpower decisions at our current sample size. This is consistent with the notion that individuals who discount rewards more steeply across effort and delay dimensions may share a broader motivational profile characterized by heightened cost sensitivity. Regulation of physical effort demands is closely tied to motivation in multiple domains such as weight loss, rehabilitation from injury and other goal states which all essentially have a future outcome, a choice architecture captured by VUS (T. Chong et al., 2016; Rodman et al., 2021). The correlation between cognitive and physical effort sensitivity is well documented across both behavioural and neural accounts of motivational valuation and should be treated as a directional signal for further

replication in a larger more adequately powered sample. The distinction of VUS with willpower related constructs positions it as an indicator of how delay and effort cost demands are jointly weighted in decision making rather than a proxy for a stable inhibitory capacity. Furthermore, VUS shows a preliminary discriminant validity but its operational utility as a measure of willpower required a larger convergent validation across more heterogenous samples and other effort modalities.

Theoretical Implications for Willpower as a Decision Process

Effort-based Delay Discounting reflects the outcome of the joint valuation process that precedes goal-oriented action specifically in how competing cost demands are resolved in favour of the effortful delayed reward. The present findings demonstrate that at high demand levels of one cost dimension, the joint influence of the other cost is attenuated. This attenuation pattern is not predicted by additive discounting models, which would anticipate a parallel downward shift in SV across effort levels rather than a systematic change in the functional slope relating delay to SV. It is, however, consistent with a multiplicative or interactive cost structure of the kind implied by Temporal Motivation Theory (Steel & König, 2006), which holds that the motivational utility of a delayed reward declines more steeply when goal-pursuit requires sustained effort. The compression gradient in Figure 4 suggests that effort is not merely subtracted from the regulatory capacity of the individual but is reorganised within the valuation surface. Relative to the purely representational cost of delay requiring mental simulation of the future, effort is a present somatic demand that directly competes with the reflective system's capacity to sustain motivational representations of the reward (Bechara, 2005). Under high cognitive load, the decision maker does not merely find the future reward less desirable but becomes progressively less sensitive to temporal distance as a parameter for action due to overwhelming computational burden of aversive effort demands. This carries a specific theoretical claim that decisions requiring willpower are not best understood as the output of isolated discount functions summed at the time point of choice, but more specifically as the product of an integrative valuation process in which the decision weight assigned to each cost demand is dynamically adjusted in response to the context of goal-directed action. Framed within this choice architecture, willpower failure does not reflect aversion to effort demands or naivety in temporal preferences, but a collapse in the capacity to tolerate sensitivity to one cost dimension when a competing dimension is highly salient. The individual operating under high cognitive demand does not simply find the delayed reward less valuable; they become less differentially sensitive to future outcomes. This lays the basis for the contextual insensitivity that attenuates the motivational gradient on which durable goal-pursuit depends which reframes the locus of willpower difficulty from impulse to integration, and from the magnitude of temptation to the functional architecture of cost representation under concurrent

demands. It is consistent with recent theoretical renditions of willpower that diverge from inhibitory strength accounts towards the emphasis of value computation and contextual calibration of regulatory engagement (D. J. Hall & Davis, 2007; Inzlicht et al., 2021; Werner & Berkman, 2024).

Finally, the theoretical reframing proposed here has direct implications for how willpower is operationalized and measured. The discriminant validity of VUS from self-reported trait willpower, delay gratification, need for cognition and action control is a theoretically coherent consequence of the structural dissociation between behavioural valuation mechanism and dispositional self-assessment. The weak correspondence between laboratory discounting measures and self-reported traits is common and well-documented in the field (Duckworth & Kern, 2011; Lange & Eggert, 2015). This reflects a genuine measurement gap rather than criterion invalidity on either side. Self-report data of constructs associated with self-regulation largely capture individual's personal beliefs about their regulatory tendencies across habitual contexts. Naturally, they do not reflect trial-level dynamics of how computational costs are integrated under concurrent demands, which is exactly what VUS captures by quantifying the aggregate landscape of effort-based delay discounting of a future outcome demanding present effortful action. This is effective in capturing the choice architecture of willpower decisions that self-report trait inventories cannot access by design. Hence, the present findings suggest that advancement in willpower research shows promise in its current gravitation towards refinement of behavioural task paradigms sensitive to integrative and contextually modulated valuation processes through which willpower is exerted and subsequently fails.

Limitations and Future Directions

While the present study offers novel insights into advancing effort-based delay discounting framework as a mechanism of willpower failures, few limitations warrant consideration that underscore the need for further research to extend and refine the proposed framework. First, the sample predominantly consisted of young adult university students, which is likely to be characterised by relatively high and homogeneous cognitive capacity, skewed delay discounting rates and motivational profiles that may be contextually shaped by their academic orientation, not representing general population (Baumard & Sperber, 2010; Harvey et al., 2024). Discounting rates for both delay and cognitive effort have shown age related differences in prior research, which was not accounted for in our sample (Wan et al., 2024; Westbrook et al., 2013). Replication in more representative samples such as older adults, clinical populations with impulse control issues, and individuals with greater heterogeneity in baseline tolerance of computational costs are recommended. Second, the stability of VUS across different time

points remains unexplored to establish its utility as a reliable individual difference measure. Test-retest reliability data are a prerequisite for any future applications of VUS in predictive or clinical contexts as the unstable reliability estimates in cognitive tasks captured as individual differences as well indexed (Hedge et al., 2018). It is also noteworthy that VUS is a descriptive aggregate behavioural measure which compresses crucial information about specific patterns of interaction between delay and effort costs in a surface to give one quantified value as the output. This information loss poses an interpretive concern, where two discounting surfaces could yield the same VUS value, where the discounting surface could be steeper due to higher sensitivity of one cost as compared to another for two individuals. In such a scenario, one VUS would not be able to differentiate between separate discounting profiles leading to a misleading interpretation of the underlying decision-making process. Since, it is a descriptive measure and not a mechanistic one, its use for group comparisons and causal interpretations should be handled with caution. Moreover, interaction effects arising from fully crossed discounting designs, particularly in intertemporal choice literature is often criticized for being mathematical artifacts rather than a true psychological representation of a phenomenon (Doyle, 2013). Although our model-free approach and a directional interaction pattern found in post hoc analysis, mitigates this concern future work should examine whether the observed interaction pattern replicates under orthogonalized rate parameter designs as recommended by Doyle et al. (2011), which would provide stronger evidence that the effect reflects psychological interaction rather than model confusability. Additional they can also potentially explore a parametric model fit for effort-based delay discounting by extending the point based numeric integration method for computing VUS as done for AUC measures for selection of candidate models (Gilroy & Hantula, 2018). Third, the Bayesian evidence for convergent validity with physical effort sensitivity was inconclusive. Although the selection of Bayesian correlation was methodologically appropriate for our current sample size in the exploratory context, it is important to acknowledge that Bayesian estimation with default priors does not automatically resolve the limitation of an under powered sample. Rather in such conditions, posterior estimates remain sensitive to prior specification and can yield more biased results than frequentist alternatives (McNeish, 2016). Since our analysis relied on default prior settings in Jamovi, the Bayes factor which reported anecdotal evidence for the association, should be treated as indicative rather than confirmatory. The planned replication study should be designed with adequate statistical power, and its Bayesian analysis should incorporate empirically derived informative priors drawn from present study's posterior distributions. Additionally, to test both convergent and discriminant predictions simultaneously, ideally including a broader battery of both behavioural and self-report measures to triangulate the construct boundaries of VUS. Finally, the present paradigm was restricted to cognitive effort as the demand manipulation, and it remains

unexplored to see if the same mutually constraining interaction pattern extends to other effort modalities. Extending the effort-based delay discounting framework to domains like physical effort using heterogenous experimental approaches would substantially strengthen the claim that the observed interaction reflects a domain-general phenomenon of value-based decision making and not limited to cognitive effort sensitivity under increasing load (A. Culbreth et al., 2023; Varma et al., 2023). To summarize, these directions reflect the theoretical and methodological trajectories any novel behavioural metric must consider before advancing or transitioning to clinical applications. The present study provides an empirically grounded starting point to explore a novel choice paradigm integral to goal-oriented motivation and effort driven impulsivity.

Conclusion

This study provides the first empirical evidence that cognitive effort and temporal delay interact in shaping reward value, with increasing effort systematically attenuating the sensitivity of subjective value delay costs. This pattern is consistent even after controlling performance indices and is associated with robust, stable individual differences. These findings challenge the conventional assumption that separable cost functions are sufficient to characterise willpower evoking decisions, further supporting the proposed reconceptualization of willpower as emergent from integrative valuation, where the relative influence of competing cost dimensions is dynamically weighted. The volume under surface (VUS) metric offers a descriptive aggregate of effort-based delay discounting behaviour with preliminary evidence of discriminant validity from willpower related traits while awaiting convergent validity. Finally, our findings motivate exploration of willpower dynamics in goal-oriented pursuits which function beyond sensitivity to time or effort individually in momentary decisions.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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