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Cognitive effort-based decision-making across experimental and daily life indices in younger

and older adults

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Abstract

Objectives: The study investigated whether cognitive effort decision-making measured via a neuroeconomic paradigm that manipulated framing (gain vs. loss outcomes), could predict daily life engagement in mentally demanding activities in both younger and older adults.

Method: Younger and older adult participants (N=310) completed the Cognitive Effort Discounting paradigm (Cog-ED), under both gain and loss conditions, to provide an experimental index of cognitive effort costs for each participant in each framing condition. A subset of participants (N=230) also completed a seven-day Ecological Momentary Assessment (EMA) protocol measuring engagement in mentally demanding daily life activities.

Results: In a large, online sample, we replicated a robust increase in cognitive effort costs among older, relative to younger, adults. Additionally, costs were found to be reduced in the loss relative to gain frame, although these effects were only reliable at high levels of task difficulty and were not moderated by age. Critically, participants who had lower effort costs in the gain frame tended to report engaging in more mentally demanding daily life activities, but the opposite pattern was observed in the loss frame. Further analyses demonstrated the specificity of reward-related cognitive motivation in predicting daily life mentally demanding activities.

Discussion: Together, these results suggest that cognitive effort costs, as measured through behavioral choice patterns in a neuroeconomic decision-making task, can be used to predict and explain engagement in mentally demanding activities during daily life among both older and younger adults.

Keywords: Cognitive effort; Ecological Momentary Assessment; Decision-making; Incentive framing

Introduction

A growing literature has suggested a motivational view of cognitive aging (Ebner et al., 2006; Hess, 2014; Swirsky & Spaniol, 2019). In particular, older adults may experience greater subjective costs associated with effortful cognitive activities, which leads to a reduced willingness to engage in such activities, unless they are found to be sufficiently motivating. Indeed, prior findings have revealed a decrease in the overall number of cognitively demanding activities older adults engage in throughout their daily lives (Hertzog et al., 2008). Likewise, physiological markers indicating higher cognitive costs are associated with reduced intrinsic motivation to perform cognitive activities (Hess et al., 2018; Queen & Hess, 2018). These changes may have important consequences for health and well-being. Maintained engagement in cognitively effortful activities has been shown to positively correlate with preservation of cognitive function in older adulthood (Hultsch et al., 1999), and may also be associated with decreased risk for developing Alzheimer's disease (Wilson et al., 2007). Such findings highlight the importance of understanding the mechanisms that contribute to age-related changes in cognitive motivation, and how these might impact older adults' daily life engagement in cognitively effortful activities.

The field of neuroeconomics offers a promising framework from which to investigate motivational changes in cognitive effort-based decision-making during older adulthood. A key focus of this framework is on value-based decision-making, in which choices are made according to subjective motivational value and reflect the integration of various sources of reward and cost (Shenhav et al., 2013). Critically, this enables the quantification of the costs of cognitive effort in economic terms, whereby motivational incentives (e.g., monetary gains or losses) are required to offset the costs of engagement in a task with high effort. As such, this framework suggests age-related motivational reprioritization might alter the relevant cost-benefit tradeoffs used to guide

decisions about whether to engage in cognitive effort. Indeed, previous work with the Cognitive Effort Discounting (Cog-ED) paradigm, which directly employs the neuroeconomic decision-making framework, supports this hypothesis. Specifically, with the Cog-ED task, a number of prior studies have repeatedly found that, relative to younger adults, older adults require greater amounts of motivational incentives to offset the costs of cognitive effort (Aschenbrenner et al., 2022; Froböse et al., 2020; Hess, Lothary, et al., 2021; Westbrook et al., 2013). Most recently it was found that these age-related changes might be at least partially related to brain amyloid accumulation (Aschenbrenner et al., 2022), which is also consistent with earlier findings that increased engagement in cognitive activities in daily life is associated with reduced beta-amyloid accumulation among healthy older adults (Landau et al., 2012).

Despite the advances in quantifying cognitive motivation across the adult life span using experimental tasks and paradigms, there has been little work that has attempted to directly relate these findings to daily life activities. Moreover, many of the findings that document age-related changes in daily activities (e.g., (Queen & Hess, 2018) are often assessed through retrospective self-report measures, rather than using reports occurring at the time of the activity (or shortly thereafter). Retrospective reports may differentially impact older adult response patterns, given declines in fluid cognitive functioning (Klumb & Baltes, 1999), and greater susceptibility to positivity biases in the recall of emotional information (Neubauer et al., 2019). In younger adults, research has shown that participants' cognitive effort costs, indexed via the Cog-ED, are positively associated with the average demand of their daily life activities, assessed via experience sampling (Culbreth et al., 2020). In other words, people who have lower Cog-ED effort costs also report engaging in more demanding daily life activities than those with higher Cog-ED effort costs. Likewise, results from a daily diary study in older adults demonstrated that

the motivation to perform activities, measured in the laboratory, was predictive of everyday

activity engagement, with the effect being specific to those activities thought to place demands

on cognitive resources (Hess et al., 2018). Nevertheless, there have been no investigations

directly comparing older and younger adults, which have used both experimental measures and

intensive micro-longitudinal assessments (i.e., experience sampling) to test for age-related

changes in cognitive motivation and their impact on daily life activities.

Furthermore, an important limitation of prior research examining cognitive effort costs

in older adults is that so far it has not considered how the framing of incentives, whether trying

to gain monetary rewards or avoid losses, affects the relevant cost-benefit tradeoffs involved in

decisions pertaining to cognitive effort. This question has high relevance for aging research,

given the theorized (Baltes, 1997; Heckhausen et al., 2019) and observed age-related

motivational shifts from gain orientation to increased focus on maintenance and loss prevention

(Ebner et al., 2006; Gong & Freund, 2020; Mustafić & Freund, 2012). Recent work has shown

that younger adults discount losses less than gains across both physical and cognitive effort

domains (Farinha & Maia, 2021; Massar et al., 2020). Moreover, a study examining gain and

loss incentive framing on physical effort-based decisions in both younger and older adults found

that older adults were more motivated to perform effortful tasks when they could avoid monetary

losses, rather than accrue monetary gains, whereas younger adults showed the opposite pattern of

results, with greater effort mobilization for gains relative to losses (Byrne & Anaraky, 2019).

However, there have not yet been parallel age group comparison studies conducted in the domain

of cognitive effort-based decision-making. This is an important gap in the literature, since it is

currently unknown whether the framing of incentives, whether gain or loss-related, also impacts

cognitive effort engagement differentially for younger and older adults (e.g., Seaman et al., 2016).

The current study investigated cognitive effort costs in younger and older adults, both in terms of gain and loss framing, and in the relationship between experimentally derived effort costs and daily life behavior. To accomplish these aims, we asked participants to complete both gain and loss versions of the Cog-ED in addition to completing a seven-day experience sampling protocol to index the mental demand of daily life activities. We pre-registered a number of key hypotheses (https://osf.io/2jtpb/). First, given age-related motivational reprioritization towards maintenance and loss prevention, in contrast to the gain-related motivational orientation often observed in younger adults (Ebner et al., 2006), we predicted that there would be an age × framing interaction, such that older adults would show steeper discounting of cognitive effort costs relative to younger adults in the gain domain, but that these age-related effort cost effects would be reduced in the loss condition. Second, as an extension of prior work in younger adults (Culbreth et al., 2020), we hypothesized that experimental measurements of cognitive effort costs in the gain domain would index the propensity of both younger and older adults to engage in mentally demanding activities in daily life, but that there would be a more tightly coupled relationship (e.g., steeper slope, stronger association) in older adults, reflecting increased selectivity in activity participation as a result of higher costs of engaging in cognitive effort (Hess & Ennis, 2012; Queen & Hess, 2018).

Methods

Participants
Participants were adults, ages 18-40 and 60-80 years, recruited through the online research platform Prolific (www.prolific.co) (Palan & Schitter, 2018). Inclusion criteria for

participation included English as native language, with no lifetime history of neurological trauma or seizures, no current use of psychotropic medications, and current residency in the United States. The sample consisted of 310 participants (190 females; M_{age}= 26.2, SD_{age}= 6.3 [younger adults]; M_{age}= 65.6, SD_{age}= 5.2 [older adults]; 1 American Indian or Alaskan Native, 13 Asian, 30 Black or African American, 252 White, 14 more than 1 race; 29 Hispanic or Latinx). A subset of these participants completed an additional experimental protocol involving the use of Ecological Momentary Assessment (EMA); N=230 (see **Supplement** for full demographic breakdown of the subsample). All experimental procedures were approved by the Washington University Human Research Protections Office prior to data collection. Participants provided informed consent and were compensated $10/hour for all study procedures, with the opportunity to gain up to an additional $8 bonus, based on the experimental tasks and $0.25 for each completed EMA survey (or a bonus payment of $15 if they completed ≥ 80% of all surveys).

The hypotheses for the discounting and EMA portions of the study were pre-registered separately. These pre-registrations, along with all data and code, can be found in the central repository for this project (https://osf.io/2jtpb). The pre-registration also contains a power analysis used to inform sample size, which indicated that a sample of 250 participants would provide 84% power [0.753, 0.906] to detect the interaction of Framing Condition and Age Group. However, because data collection was conducted online in batches of participants (with the anticipation of drop-out across the discounting and EMA study components), the final sample size (N=310) exceeded the minimum sample size needed to detect this effect.

Design

Cognitive Effort Discounting

To examine the relationship between experimental measures of cognitive effort costs and daily life mental demand, we employed the Cog-ED as an established experimental paradigm to enable quantitative estimation of the subjective value (i.e., cost) of cognitive effort in older and younger adults (Aschenbrenner et al., 2022; Froböse et al., 2020; Hess, Lothary, et al., 2021; Westbrook et al., 2013). Multiple prior studies have demonstrated that the Cog-ED provides stable and consistent within-person measurements across different cognitive domains and time in both younger and older adults (Aschenbrenner et al., 2022; Crawford et al., 2022; Westbrook et al., 2019). Furthermore, even when controlling for the effects of individual differences in task performance and working memory capacity on discounting across distinct cognitive domains (Aschenbrenner et al., 2022; Crawford et al., 2022), participants in both age groups still show strong domain-general cognitive effort discounting. Together, this prior work suggests that the Cog-ED is a suitable tool for assessing the trait-like tendency to engage in cognitive effort in older as well as younger adults, and does not merely reflect other stable individual differences, such as working memory capacity.

In the Cog-ED, participants are first familiarized with the N-back working memory task (Familiarization Phase), performing task levels that vary in mental demand (levels N=1-4, 20 trials/level). Following each run of the N-back, participants completed self-reported ratings of the mental demand, physical demand, temporal demand, effort, frustration, and performance from the preceding task block using the NASA Task Load Index (TLX; Hart, 2006). Participants provided their responses using a visual analog scale ranging from 1 (very low) - 21 (very high). These ratings helped to serve as a manipulation check and were used in control analyses to

examine the effect of self-reported frustration and performance on effort discounting (see **Supplement)**.

After experiencing and practicing the N-back task at each load level during the familiarization phase, the decision-making phase occurs, in which participants must make repeated choices about whether to repeat performance of a higher load-level of the N-back (e.g., 4-back) for a larger reward, or instead perform the easiest load level (1-back) for a smaller reward. The offer for the smaller reward is then stepwise titrated until participants are indifferent between the two offers (i.e., they would choose either offer equally). These indifference points estimate the "cost" of cognitive effort. In other words, the indifference point reflects the amount of money an individual is willing to forgo to avoid performing the more effortful task. For continuity with the prior literature examining discounting in many domains, including time, probability, and effort (e.g., Green & Myerson, 2004; Seaman et al., 2018), we also inter-changeably use the terminology of subjective value to refer to this indifference point. For example, if a participant was making choices between performing the 1-Back vs. the 3-Back with a starting amount of $4 for the 3-Back and the indifference point was equal to $1 after the calibration trials, the subjective value estimate for this pairing would be 0.25 (i.e., the indifference point divided by the fixed, large-reward value for that pairing).

Critically, participants were informed that one of their choices would be used to determine compensation, and that in the final 'performance phase' of the experiment, they would be asked to repeat the task they chose, for the amount of money offered (i.e., $2 for the 2-back). It is important to note that, consistent with prior work using this paradigm (Aschenbrenner et al., 2022; Crawford et al., 2022; Culbreth et al., 2020; Westbrook et al., 2013), compensation _was not based on performance_ from the familiarization phase. Rather, participants were told that in

order to successfully earn the money for repeating the chosen task, they would need to maintain their effort from the familiarization block when repeating the task block (in actuality, all participants earned the bonus money).

In addition to performing the gain version of the Cog-ED, participants were asked to perform the Cog-ED in a loss context. The discounting procedure was identical to the gain condition, except that participants were first given an initial $5 endowment, and then asked to make decisions between low-effort tasks associated with larger monetary losses and high-effort tasks with smaller monetary losses (see **Figure 1** for an example). As in the gain condition, participants were informed that, in the performance phase, one of their choices from the decision-making phase would be selected for them to repeat for the amount of reward offered on that trial (i.e., participants received compensation for the randomly selected trial across both gain and loss effort discounting conditions at the conclusion of the experiment). The order of task administration of the discounting tasks (gain, loss) was counter-balanced across participants.

Daily Life Sampling

To examine the relationships between the costs of cognitive effort (i.e., Cog-ED subjective value estimates) and the mental demand of activities in daily life, we invited participants to also complete our EMA protocol. After completing the Cog-ED, participants completed a tutorial describing the necessary steps to download the EMA app (Expiwell; https://www.expiwell.com) and complete the EMA surveys. First, participants were instructed to download Expiwell on their phone and answer a series of questions (e.g., what initial start date did they enter into the app), to ensure that they could understand and follow the instructions for downloading the app and setting up the delivery of the EMA surveys. Next, participants were taken through the structure and content of the EMA survey (including all survey items) and were

asked to answer questions about the contents of the survey to ensure proper understanding before beginning the protocol.

All procedures were completed remotely, online, with the opportunity to message the experimenters if participants had any questions or concerns. If participants did not answer the questions successfully (N= 28; 41 additional participants did not enter any information about EMA procedures via the questionnaires at all) or did not have mobile phones that were compatible with the EMA software (N = 11), their data were not included in the final analyses for this portion of the study. As a part of the 7-day EMA protocol, participants received six randomly prompted surveys per day over a fixed twelve-hour window, with approximately two hours in between each survey, for a total of 42 assessment points. Due to the nature of online testing, all participants received prompts during the same twelve-hour window; this was not customized to each participant.

For each survey, participants received a notification containing a link to complete the survey through Qualtrics (Qualtrics, Provo, UT). Upon clicking on the survey link, they were asked to record the activities they engaged in, during the past two hours, from a list of activities. Following this prompt, a subset of up to three of the previously endorsed activities were randomly sampled for participants to answer additional questions about. Specifically, these questions asked participants to rate how mentally demanding each of these activities was (using a rating scale ranging from "Not at all" (1) to "Extremely" (5)) and their level of motivation and enjoyment toward each activity. The survey items indexing daily life activities and mental demand were adapted from previous work in younger adults (Culbreth et al., 2020), which aimed to assess the relationships between the costs of engaging in effort (i.e., using discounting paradigms like the Cog-ED) and daily life experiences using EMA. In addition, participants were

asked to answer additional questions about their current affective state at the time of each survey and who they are interacting with at the time of the survey (see **Appendix 1** for detailed information on the structure and content of the survey); however, these data are not analyzed here. Participants were allotted 30 minutes to begin the survey after each notification from the app, after which time their responses were not recorded. If participants did not complete the survey within fifteen minutes after the initial notification, they automatically received a reminder to complete the survey. Overall, participants completed 74.5% of all surveys delivered.

Analysis

Cognitive Effort Discounting

We extracted subjective value estimates from both the gain and loss discounting conditions across all participants. If a participant failed to complete both versions of the Cog-ED, their data was not included in the analyses for this study (N= 4). Prior to performing statistical analyses, we transformed the subjective value estimates from the loss condition by multiplying them by -1 to keep the scaling consistent across the two incentive domains. To test hypotheses related to the age × framing interaction, we entered task level, condition, age group, and their interactions as fixed effects into a multilevel model with subjective value as the dependent variable: Subjective Value ~ Task Level*Condition*Age Group + (1 | Participant); task level was contrast coded (2-back = -1, 3-back = 0, 4-back = 1), whereas condition (Gain = 0, Loss = 1) and age group (Young = 0, Old = 1) were dummy coded. In addition, we tested for the effects of task order because the order of conditions was counter-balanced across participants; task order was entered into the model as a dummy coded variable (Gain first = 0, Loss first = 1), although this control analysis was not initially pre-registered.

Daily Life Sampling

In the present experiment, the EMA data are inherently nested (i.e., EMA data points occur within individuals). Thus, to account for the dependences in this data structure we conducted our analyses using multilevel models. To test our central hypothesis that there is a positive relationship between cognitive effort costs and daily life mental demand, we included the subjective value estimates calculated through the gain and loss versions of the Cog-ED (measuring individual participants' willingness to expend cognitive effort) as centered level-2 variables in addition to controlling for age group (dummy coded; Young = 0, Old = 1), time of day (contrast coded; Morning = -1, Afternoon = 0, Evening = 1) and day of the week (numeric coding ranging from 0-6; Monday = 0, Sunday = 6). The dependent variable for the multilevel model was the mean of the mental demand ratings at each measurement occasion; participants supplied up to three mental demand ratings at each time point, so these estimates were averaged to create a single mental demand value for each measurement occasion. Furthermore, we conducted additional analyses to test for the interactions between age group and subjective value estimates to test our hypothesis that the strength of these associations is moderated by age group.

We also conducted additional exploratory analyses aimed at assessing whether there is a unique effect of reward motivation (i.e., sensitivity to engaging in cognitive effort for gains vs. losses) on daily life mental demand. In all the multilevel models reported in this manuscript, we included the intercept as a random effect; all other covariates were entered as fixed effects. All multilevel models were conducted with the packages *lme4* (version 1.1-27.1; Bates et al., 2015) and *lmerTest* (version 3.1-3; Kuznetsova et al., 2017), in R version 4.1.0 (RRID:SCR_001905; R CoreTeam, 2018) and effects are reported as the estimate from the model with 95% confidence intervals and the corresponding test statistic and p-value.

Results

Cognitive Effort Discounting

Replicating previous work conducted in the laboratory environment (e.g., Culbreth et al., 2020; Westbrook et al., 2013), but here with an online sample, we found that N-back task load was associated with decreased subjective value estimates, indicating that cognitive effort costs progressively increased with increased task difficulty (i.e., 4-back > 3-back > 2-back; B = -0.14 [-.16, -.11], t = -10.37, p < 0.001; **Figure 2**). Critically, we also extended prior results (Westbrook et al., 2013), in demonstrating with a large and well-powered sample, a robust age effect, B = -0.12 [-0.18, -0.06], t = -3.82, p < 0.001. Older adults had lower subjective value estimates overall (M = 0.51, SD = 0.38) as compared to younger adults (M = 0.64, SD = 0.33), reflecting higher cognitive effort costs. Control analyses indicated that these age effects on cognitive effort costs could not be explained by key self-reported ratings of frustration or performance (from the NASA TLX; **Supplement**).

In addition, we also observed an effect of framing condition, B = 0.07 [.04, .10], t = 4.33, p < 0.001. Subjective value estimates were higher in the loss domain (M = 0.61, SD = 0.34) relative to the gain domain (M = 0.55, SD = 0.38), indicating that participants were more willing to choose to engage in cognitive effort for monetary incentives that were framed as avoiding larger potential losses versus obtaining higher gains. Interestingly, the framing effect interacted with task load, B= 0.05 [.01, .08], t = 2.53, p = 0.011. Specifically, there was no overall difference in discounting between gain and loss conditions for low (2-back; t(309) = -1.42 [-0.65, 0.01], p = 0.158) or medium levels of effort (3-back; t(309) = -1.31 [-0.06, 0.01], p = 0.190), but there was a difference at the highest level of effort (4-back; t(309) = -6.15 [-0.16, -0.08], p < 0.001). These results indicate that, only at the highest level of task difficulty (i.e., 4-back), was

subjective value was higher in the loss condition (*M* = 0.56, *SD* = 0.38) than in the gain condition (*M* = 0.44, *SD* = 0.38).

However, the pre-registered age group × framing interaction was not significant, *B*= -0.02 [-.06, .02], *t* = -0.88, *p* = 0.379, nor were any of the other interactions in the model, *p*s> 0.340 (see **Table 1**). As an additional control, we tested for the effects of task order on cognitive effort discounting. Task order was not a significant predictor of subjective value, *B*= -0.02 [-.08, .04], *t* = -0.57, *p* = 0.570; all other previously reported effects remained significant, *p*s < 0.011, after including task order into the model (**Table 1**). Further summary of N-Back task performance and its effects on subjective value estimates can be found in the **Supplement**.

Daily Life Mental Demand

On average, participants endorsed engaging in approximately two activities in the previous two hours (*M* = 2.18, *SD* = 1.25, range = 1-13). Further descriptive information pertaining to the mental demand ratings and activities of the sample (e.g., person means, iSD) can be found in the **Supplement**. Prior to conducting the multilevel models described above, we ran a null model of the mental demand ratings and extracted the intraclass correlation coefficient (ICC) in order to the partition the within- and between-person variance. The ICC for the null model was 0.226, suggesting that daily life mental demand consisted of both within- (77.4%) and between-person variance (22.6%), providing a sound rationale to conduct our planned analyses examining the contribution of between-person differences in the costs of cognitive effort and within-person daily life variables (e.g., time of day, day of survey) on daily life mental demand.

We observed a main effect of age group, *B* = -0.14 [-0.26, -0.02], *t* = -2.24, *p* = 0.025, demonstrating that older adults engaged in overall less mentally demanding daily activities, after controlling for the other model covariates (see **Table 2** for full model output). Further, we

replicated and extended the findings of Culbreth et al. (2020), in that subjective value of cognitive effort was a significant predictor of engagement in mentally demanding activities, $B = 0.75$ [0.42, 1.09], $t = 4.38$, $p < 0.001$. In other words, participants who had a higher subjective value of cognitive effort in the gain domain (i.e., lower cognitive effort costs) tended to report engaging in more mentally demanding daily life activities. Although cognitive effort costs in the loss domain were positively correlated with the gain domain, in both younger, $r = 0.58$ [0.47, 0.68], $t = 9.14$, $p < 0.001$, and older adults, $r = 0.54$ [0.41, 0.64], $t = 7.66$, $p < 0.001$, they exhibited an opposite pattern of association with daily life activities, $B = -1.01$ [-1.39, -0.63], $t = -5.19$, $p < 0.001$. Specifically, participants who had a higher subjective value of effort in the loss domain (i.e., greater willingness to engage in cognitive effort to avoid losing money) engaged in *less* rather than more mentally demanding activities in daily life.

We did observe an interaction between cognitive effort costs and age group across both gain, $B = -0.49$ [-0.93, -0.05], $t = -2.16$, $p = 0.030$ (**Figure 3a**) and loss incentive domains, $B = 0.70$ [0.21, 1.18], $t = 2.81$, $p = 0.005$ (**Figure 3b**). However, these effects were counter to our pre-registered prediction, in that younger adults exhibited a tighter coupling of the costs of cognitive effort and daily life mental demand engagement in both gain and loss incentive contexts, relative to older adults (see **Table 2**). Moreover, as an additional control, we found that the effects of subjective value (gain and loss) and its interactions with age group remained after controlling for the number of activities completed at each measurement occasion and the total number of surveys completed over the sampling period, $ps < 0.026$. Further control analyses suggest that these effects were not due to fluctuations in energy level. Including self-reported ratings of arousal or sluggishness in the period prior to engaging in activities did not alter the relationship between cognitive effort costs (as measured by the Cog-ED) and the mental demand

of such activities (even though sluggishness did predict a generalized reduction in engagement with demanding activities; see **Supplement** for further details and discussion of both sets of control analyses).

To further investigate the gain and loss patterns, we conducted an exploratory analysis, to compare participants who were more reward motivated, in that they exhibited lower cognitive effort costs in the gain relative to loss domain (i.e., gain > loss subjective value), with those who were more loss motivated (i.e., loss > gain subjective value). Strikingly, reward motivated individuals tended to report more engagement in mentally demanding daily life activities, $B =$ 0.54 [0.26, 0.81], $t = 3.78$, $p < 0.001$, and this was not moderated by age group, $B = -0.30$ [-0.65, 0.05], $t = -1.69$, $p = 0.090$; see **Supplement** for related exploratory analyses.

Discussion

We found compelling evidence for the linkage between experimentally derived measures of cognitive effort costs and naturalistic assessment of engagement in daily life mentally demanding activities across both younger and older adults. As an extension of prior work (Culbreth et al., 2020), but with a large online sample including older as well as younger adults, we found that in both age groups, individuals who exhibited lower effort costs (in the gain domain) tended to have higher levels of engagement in mentally demanding activities in daily life. Strikingly, the opposite pattern was observed in the loss domain, wherein participants who were the most likely to engage in cognitive effort to avoid losing money actually had lower levels of engagement in mentally demanding activities in daily life. Importantly, both effects explained unique variance in the multilevel model predicting daily life mental demand when entered simultaneously, which suggests that the cognitive effort costs measured across both incentive domains tap into distinct aspects of daily life behavior. Furthermore, exploratory

analyses revealed a specific relationship to reward-related cognitive motivation, as individuals exhibiting higher subjective value for cognitive effort to obtain reward outcomes (rather than to avoid losses), also reported higher engagement in mentally demanding activities in daily life.

Furthermore, the results clearly showed that older adults discount cognitive effort overall more than younger adults, providing additional empirical support for age-related increases in the subjective costs of cognitive effort, in a large, online sample. As a novel extension of this prior work, both younger and older adults completed discounting across loss incentive framing conditions in addition to the gain framing (i.e., the original version of the Cog-ED). We observed that participants tend to discount losses less than gains overall, however, this effect appeared to be driven by differences between gain and loss discounting at the highest level of task difficulty; both younger and older adults have higher subjective value estimates (i.e., less discounting) at the highest level of task difficulty, but not at lower levels of task difficulty. This pattern of results replicates and extends prior work in younger adults using a similar cognitive effort discounting paradigm, which showed that younger adults discount cognitive effort less in loss incentive contexts only at high levels of task difficulty (Massar et al., 2020).

Contrary to our pre-registered predictions, we did not observe any interactions with age group in terms of the framing effect. This suggests that younger and older adults show similar patterns of cognitive effort discounting across gain and loss incentive contexts, with older adults having overall higher cognitive effort costs. Although this pattern of results contrasts prior work in other research domains, multiple meta-analyses have found no differences in gain and loss framed decision making across older and younger adults (Best & Charness, 2015; Mata et al., 2011), which might suggest that the nature of these age-related motivational shifts is highly task specific. Conversely, we did find age-related interactions in the relationship between cognitive

effort costs and daily life activity. These were also counter to our pre-registered predictions, in that this relationship was stronger for younger relative to older adults, in both gain and loss domains. Interestingly, however, the multilevel modeling indicated that not only were there overall age-related reductions in daily life mentally demanding activities, but that much of this age-related variance could be accounted for by cognitive effort costs, which were significantly increased in older adults.

Future Directions and Limitations

Together, these findings provide a strong foundation and clear guidance regarding promising future research directions. For example, future studies could use the EMA data to test for the subsequent affect experienced after engaging in mentally demanding activities, and whether such effects are moderated by age. These results could help to clarify the affective component of age-related cognitive effort costs (i.e., investigating the socioemotional selectivity account of mental demand engagement in daily life; Charles & Carstensen, 2010). Likewise, the results suggest the potential of experimental interventions aimed at reducing cognitive effort costs, as these might be instrumental in increasing older adults' daily life engagement in mentally demanding activities, with the associated protective effects that this confers. Furthermore, it remains an open question as to how cognitive effort costs fluctuate within-person across time and whether such metrics can be used to predict the types of activities people choose to engage in in daily life. Relatedly, a final direction of high potential is to rigorously test the relative contributions of between-person characteristics (e.g., cognitive ability and motivation; Queen & Hess, 2018) and dynamic within-person fluctuations during daily life, such as affect and social interactions, to better determine how they respectively account for variation in effortful activities across the adult life span.

The findings also suggest the importance of discovering the biological mechanisms associated with increased cognitive effort costs in older adults. Prior fMRI studies in younger adults have pointed to the brain valuation network, with key nodes in ventromedial prefrontal cortex and striatum, as being critical for cognitive effort-based decision-making (Lopez-Gamundi et al., 2021; Westbrook et al., 2019), while PET studies have implicated the dopamine system (Westbrook et al., 2020, 2021). However, a heterogenous pattern of findings have been found in older adults, with both preservation of fMRI valuation signals (Seaman et al., 2018), and maintenance/increases in striatal dopamine synthesis capacity (Karrer et al., 2017), but also decreases in PET radioligand indices of striatal D2 receptor binding potential (Berry et al., 2018; Seaman et al., 2019). These findings suggest that assessing the function of valuation-related regions in older adults, using a combination of PET and fMRI modalities, will be most informative in providing insights into the nature of age-related increases in cognitive effort costs. Moreover, acquiring these neural measures could also shed light on individual differences in discounting behaviors across gain and loss incentive contexts that contribute to the observed pattern of daily life behaviors reported in this manuscript (for review, see Yee et al., 2021). Finally, studies on the relationship of cognitive effort costs to daily life mental activities should also assess AD-related biomarkers (e.g., beta-amyloid) in older adults, as recent work has indicated that the presence of such biomarkers may contribute to age-related increases in effort cost (Aschenbrenner et al., 2022).

Although a clear strength of the study was its large sample size, the online nature of data collection (which facilitated the sample size increase) was also a potential source of limitation. With online data collection, participant samples may be distinct in make-up compared with in-person studies, experimenter control over task performance is clearly lower, and the

experimental session time may also need to be significantly reduced (as was done here, to 1 hour), limiting the number of additional measures that could be collected. Consequently, we did not collect health-related measures or measures of job complexity, which are likely to be an important factor when assessing the mental demand of daily life activities, especially across age groups (e.g., Hess et al., 2012); nor were we able to use standard cognitive screening instruments given the remote, online task administration. Likewise, we did not acquire other cognitive measures that could enable rigorous tests of the contribution of cognitive ability to cognitive effort costs in younger and older adults. Nonetheless, we did conduct analyses controlling for N-Back performance (accuracy and RT) and self-reported ratings of performance and frustration in the models predicting subjective value and all effects remained when controlling for these variables, suggesting that cognitive ability and self-reported performance metrics do not fully explain cognitive effort costs (see **Supplement**). It is also important to acknowledge that the present study used an extreme group design, which could exaggerate the effect of age on these estimates, relative to the richer age effects that could emerge with a continuous life span sample.

Conclusion

Despite its limitations, the present study provides some of the first data linking experimental assessments of cognitive motivation with the daily life behavior in younger and older adults, capitalizing on a sample that was many times larger than any of the previous work conducted in this domain. We confirmed that older adults exhibit increased cognitive effort costs, as assessed by the Cog-ED decision-making task, and in both gain and loss domains. We further demonstrated that ecological validity of these findings by demonstrating that older adults also exhibited clear reductions in engagement in mentally demanding activities during daily life. These effects were strongly linked to the Cog-ED, with independent contributions of both the

gain and loss-related effort cost measures, while also suggesting a specific role for reward-related cognitive motivation in promoting daily life effortful activity engagement. Indeed, the results are consistent with the idea that it is the increase in cognitive effort costs experienced by older adults that leads them to reduce engagement in mentally demanding activities in their daily lives. Taken together, these results suggest that the estimates of cognitive effort costs obtained with the Cog-ED task, in both gain and loss incentive contexts, provide a sensitive metric that can be used to help understand how older and younger adults experience daily life activities, as well as how these experiences might change with increasing age.

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Reference

Aschenbrenner, A. J., Crawford, J. L., Peelle, J. E., Fagan, A., Benzinger, T., Morris, J. C.,

Hassenstab, J., & Braver, T. S. (2022). Increased cognitive effort costs in healthy aging and

preclinical Alzheimer disease. *PsyArXiv.* https://doi.org/10.31234/osf.io/pfz6e

Baltes, P. B. (1997). On the incomplete architecture of human ontogeny. Selection, optimization,

and compensation as foundation of developmental theory. *The American Psychologist*, *52*(4),

366–380. https://doi.org/10.1037/0003-066x.52.4.366

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models

Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Berry, A. S., Jagust, W. J., & Hsu, M. (2018). Age-related variability in decision-making:

Insights from neurochemistry. *Cognitive Affective Behavioral Neuroscience*, *19*(3), 415–434.

https://doi.org/10.3758/s13415-018-00678-9

Best, R., & Charness, N. (2015). Age differences in the effect of framing on risky choice: A

Meta-Analysis. *Psychology and Aging*, *30*(3), 688–698. https://doi.org/10.1037/a0039447

Byrne, K. A., & Anaraky, R. G. (2019). Strive to win or not to lose? Age-related differences in

framing effects on effort-based decision-making. *The Journals of Gerontology: Series B*,

75(10), 2095–2105. https://doi.org/10.1093/geronb/gbz136

Charles, S. T., & Carstensen, L. L. (2010). Social and emotional aging. *Annual Review of*

Psychology, *61*, 383–409. https://doi.org/10.1146/annurev.psych.093008.100448

Crawford, J. L., Eisenstein, S. A., Peelle, J. E., & Braver, T. S. (2022). Domain-general cognitive motivation: Evidence from economic decision-making – Final Registered Report. *Cognitive Research: Principles and Implications*, *7*(1), 23. https://doi.org/10.1186/s41235-022-00363-z

Culbreth, A. J., Westbrook, A., Braver, T. S., & Barch, D. M. (2020). Effort in daily life: Relationships between experimental tasks and daily experience. *Motivation Science*, *6*(3), 303–308. https://doi.org/10.1037/mot0000159

Ebner, N. C., Freund, A. M., & Baltes, P. B. (2006). Developmental changes in personal goal orientation from young to late adulthood: From striving for gains to maintenance and prevention of losses. *Psychology and Aging*, *21*(4), 664–678. https://doi.org/10.1037/0882-7974.21.4.664

Farinha, A. C., & Maia, T. V. (2021). People exert more effort to avoid losses than to obtain gains. *Journal of Experimental Psychology: General*, *150*(9), 1837–1853. https://doi.org/10.1037/xge0001021

Froböse, M. I., Westbrook, A., Bloemendaal, M., Aarts, E., & Cools, R. (2020). Catecholaminergic modulation of the cost of cognitive control in healthy older adults. *PLoS One*, *15*(2), e0229294-26. https://doi.org/10.1371/journal.pone.0229294

Gong, X., & Freund, A. M. (2020). It is what you have, not what you lose: Effects of perceived gains and losses on goal orientation across adulthood. *The Journals of Gerontology: Series B*, *75*(10), 2106–2111. https://doi.org/10.1093/geronb/gbz163

Green, L., & Myerson, J. (2004). A discounting framework for choice with delayed and probabilistic reward. *Psychological Bulletin*, *130*, 769–792.

Hart, S. G. (2006). NASA-task load index (NASA-TLX); 20 years later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *50*, 904–908.

Heckhausen, J., Wrosch, C., & Schulz, R. (2019). Agency and motivation in adulthood and old age. *Annual Review of Psychology*, *70*(1), 191–217. https://doi.org/10.1146/annurev-psych-010418-103043

Hertzog, C., Kramer, A. F., & Wilson, R. S. (2008). Enrichment effects on adult cognitive development can the functional capacity of older adults be preserved and enhanced? *Science in the Public*, *9*(1), 1–65. https://doi.org/10.1111/j.1539-6053.2009.01034.x

Hess, T. M. (2014). Selective engagement of cognitive resources. *Perspectives on Psychological Science : A Journal of the Association for Psychological Science*, *9*(4), 388–407. https://doi.org/10.1177/1745691614527465

Hess, T. M., Emery, L., & Neupert, S. D. (2012). Longitudinal relationships between resources, motivation, and functioning. *The Journals of Gerontology: Series B*, *67B*(3), 299–308. https://doi.org/10.1093/geronb/gbr100

Hess, T. M., & Ennis, G. E. (2012). Age differences in the effort and costs associated with cognitive activity. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *67*(4), 447–455. https://doi.org/10.1093/geronb/gbr129

Hess, T. M., Freund, A. M., & Tobler, P. N. (2021). Effort mobilization and healthy aging. *The Journals of Gerontology: Series B*, *76*(Supplement_2), S135–S144. https://doi.org/10.1093/geronb/gbab030

Hess, T. M., Growney, C. M., O'Brien, E. L., Neupert, S. D., & Sherwood, A. (2018). The role of cognitive costs, attitudes about aging, and intrinsic motivation in predicting engagement in everyday activities. *Psychology and Aging*, *33*(6), 953–964. https://doi.org/10.1037/pag0000289

Hess, T. M., Lothary, A. F., O'Brien, E. L., Growney, C. M., & DeLaRosa, J. (2021). Predictors of engagement in young and older adults: The role of specific activity experience. *Psychology and Aging*, *36*(2), 131–142. https://doi.org/10.1037/pag0000561

Hultsch, D. F., Hertzog, C., Small, B. J., & Dixon, R. A. (1999). Use it or lose it: Engaged lifestyle as a buffer of cognitive decline in aging? *Psychology and Aging*, *14*(2), 245–263. https://doi.org/10.1037/0882-7974.14.2.245

Karrer, T. M., Josef, A. K., Mata, R., Morris, E. D., & Samanez-Larkin, G. R. (2017). Reduced dopamine receptors and transporters but not synthesis capacity in normal aging adults: a meta-analysis. *Neurobiology of Aging*, *57*, 36–46. https://doi.org/10.1016/j.neurobiolaging.2017.05.006

Klumb, P. L., & Baltes, M. M. (1999). Validity of retrospective time-use reports in old age. *Applied Cognitive Psychology*, *13*(6), 527–539. https://doi.org/10.1002/(SICI)1099-0720(199912)13:6<527::AID-ACP614>3.0.CO;2-1

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*(13). https://doi.org/10.18637/jss.v082.i13

Landau, S. M., Marks, S. M., Mormino, E. C., Rabinovici, G. D., Oh, H., O'Neil, J. P., Wilson, R. S., & Jagust, W. J. (2012). Association of lifetime cognitive engagement and low β-amyloid deposition. *Archives of Neurology*, *69*(5), 623–629. https://doi.org/10.1001/archneurol.2011.2748

Lopez-Gamundi, P., Yao, Y.-W., Chong, T. T.-J., Heekeren, H. R., Herrero, E. M., & Pallares, J. M. (2021). The neural basis of effort valuation: A meta-analysis of functional magnetic resonance imaging studies. *Neuroscience & Biobehavioral Reviews*, *131*, 1275–1287. https://doi.org/10.1016/j.neubiorev.2021.10.024

Massar, S. A. A., Pu, Z., Chen, C., & Chee, M. W. L. (2020). Losses motivate cognitive effort more than gains in effort-based decision making and performance. *Frontiers in Human Neuroscience*, *14*, 217–219. https://doi.org/10.3389/fnhum.2020.00287

Mata, R., Josef, A. K., Samanez-Larkin, G. R., & Hertwig, R. (2011). Age differences in risky choice: a meta-analysis. *Annals of the New York Academy of Sciences*, *1235*(1), 18–29. https://doi.org/10.1111/j.1749-6632.2011.06200.x

Mustafić, M., & Freund, A. M. (2012). Means or outcomes? Goal orientation predicts process and outcome focus. *European Journal of Developmental Psychology*, *9*(4), 493–499. https://doi.org/10.1080/17405629.2012.661411

Neubauer, A. B., Scott, S. B., Sliwinski, M. J., & Smyth, J. M. (2019). How was your day? Convergence of aggregated momentary and retrospective end-of-day affect ratings across the adult life span. *Journal of Personality and Social Psychology*, 1–20. https://doi.org/10.1037/pspp0000248

Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22–27. https://doi.org/10.1016/j.jbef.2017.12.004

Queen, T. L., & Hess, T. M. (2018). Linkages between resources, motivation, and engagement in everyday activities. *Motivation Science*, *4*(1), 26–38. https://doi.org/10.1037/mot0000061

R Core Team (2018). *R: A language and environment for statistical computing*. https://www.R-project.org/

Seaman, K. L., Brooks, N., Karrer, T. M., Castrellon, J. J., Perkins, S. F., Dang, L. C., Hsu, M., Zald, D. H., & Samanez-Larkin, G. R. (2018). Subjective value representations during effort, probability and time discounting across adulthood. *Social Cognitive and Affective Neuroscience*, *11*(3), 1–11. https://doi.org/10.1093/scan/nsy021

Seaman, K. L., Gorlick, M. A., Vekaria, K. M., Hsu, M., Zald, D. H., & Samanez-Larkin, G. R. (2016). Adult age differences in decision making across domains: Increased discounting of social and health-related rewards. *Psychology and Aging*. https://doi.org/10.1037/pag0000131.supp

Seaman, K. L., Smith, C. T., Juarez, E. J., Dang, L. C., Castrellon, J. J., Burgess, L. L., Juan, M. D. S., Kundzicz, P. M., Cowan, R. L., Zald, D. H., & Samanez-Larkin, G. R. (2019).

Differential regional decline in dopamine receptor availability across adulthood: Linear and nonlinear effects of age. *Human Brain Mapping*, *40*(10), 3125–3138. https://doi.org/10.1002/hbm.24585

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control: an integrative theory of anterior cingulate cortex function. *Neuron*, *79*(2), 217–240. https://doi.org/10.1016/j.neuron.2013.07.007

Swirsky, L. T., & Spaniol, J. (2019). Cognitive and motivational selectivity in healthy aging. *Wiley Interdisciplinary Reviews: Cognitive Science*, *24*, e1512-12. https://doi.org/10.1002/wcs.1512

Westbrook, A., Bosch, R. van den, Määttä, J. I., Hofmans, L., Papadopetraki, D., Cools, R., & Frank, M. J. (2020). Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. *Science*, *367*(6484), 1362–1366. https://doi.org/10.1126/science.aaz5891

Westbrook, A., Frank, M. J., & Cools, R. (2021). A mosaic of cost–benefit control over cortico-striatal circuitry. *Trends in Cognitive Sciences*. https://doi.org/10.1016/j.tics.2021.04.007

Westbrook, A., Kester, D., & Braver, T. S. (2013). What is the subjective cost of cognitive effort? Load, trait, and aging effects revealed by economic preference. *PLoS One*, *8*(7), e68210. https://doi.org/10.1371/journal.pone.0068210

Westbrook, A., Lamichhane, B., & Braver, T. (2019). The subjective value of cognitive effort is encoded by a domain-general valuation network. *The Journal of Neuroscience*, *39*(20), 3934–3947. https://doi.org/10.1523/jneurosci.3071-18.2019

Wilson, R. S., Scherr, P. A., Schneider, J. A., Tang, Y., & Bennett, D. A. (2007). Relation of

cognitive activity to risk of developing Alzheimer disease. *Neurology*, *69*(20), 1911–1920.

https://doi.org/10.1212/01.wnl.0000271087.67782.cb

Yee, D. M., Leng, X., Shenhav, A., & Braver, T. S. (2021). Aversive motivation and cognitive

control. *Neuroscience & Biobehavioral Reviews*, *133*, 104493.

https://doi.org/10.1016/j.neubiorev.2021.12.016

Table 1.

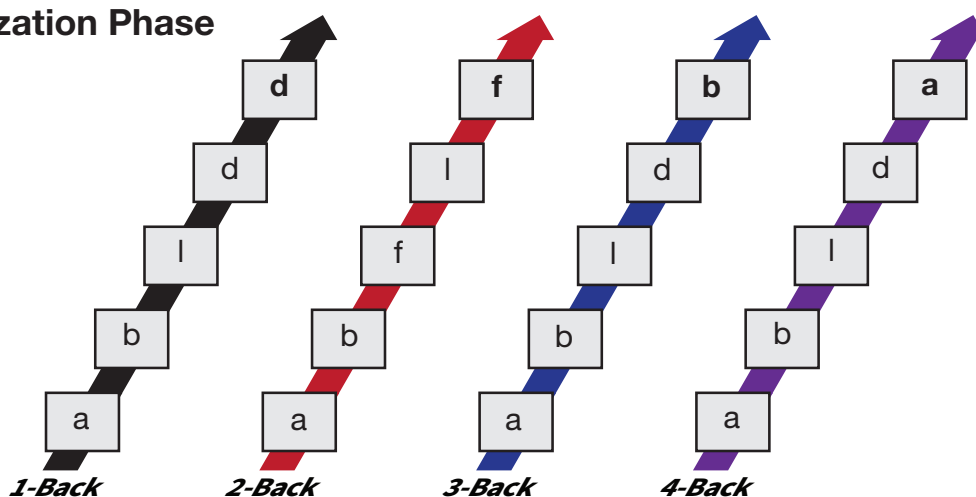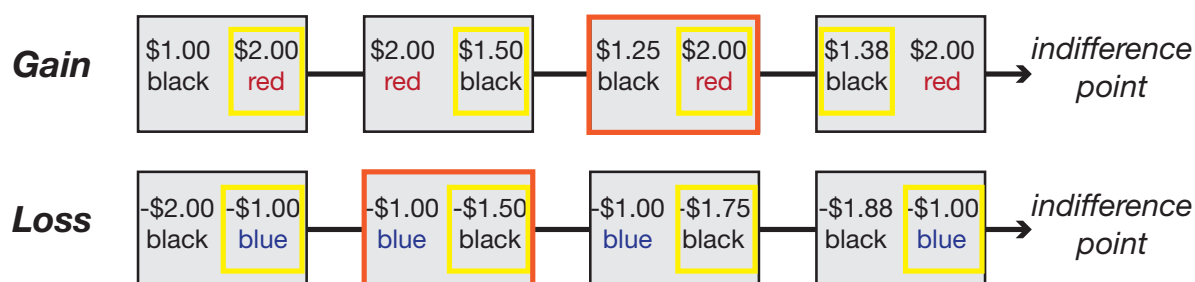| Predictors	Subjective Value				Subjective Value			
	Estimates	CI	Statistic	p	Estimates	CI	Statistic	p
(Intercept)	0.61	0.57 – 0.65	27.92	**<0.001**	0.62	0.57 – 0.67	23.78	**<0.001**
Task Level	-0.14	-0.16 – -0.11	-10.37	**<0.001**	-0.14	-0.16 – -0.11	-10.37	**<0.001**
Condition	0.07	0.04 – 0.10	4.33	**<0.001**	0.07	0.04 – 0.10	4.33	**<0.001**
Age Group	-0.12	-0.18 – -0.06	-3.82	**<0.001**	-0.12	-0.18 – -0.06	-3.79	**<0.001**
Task Level * Condition	0.05	0.01 – 0.08	2.53	**0.011**	0.05	0.01 – 0.08	2.53	**0.011**
Task Level * Age Group	0.02	-0.02 – 0.06	0.95	0.340	0.02	-0.02 – 0.06	0.95	0.340
Condition * Age Group	-0.02	-0.06 – 0.02	-0.88	0.379	-0.02	-0.06 – 0.02	-0.88	0.379
Task Level* Condition* Age Group	-0.00	-0.06 – 0.05	-0.10	0.919	-0.00	-0.06 – 0.05	-0.10	0.919
Task Order					-0.02	-0.08 – 0.04	-0.57	0.570

Note. Task level was contrast coded (2-back = -1, 3-back = 0, 4-back = 1), whereas condition (Gain = 0, Loss = 1), age group (Young = 0, Old = 1), and task order (Gain first = 0, Loss first = 1) were entered into the model as dummy coded variables.

Table 2.

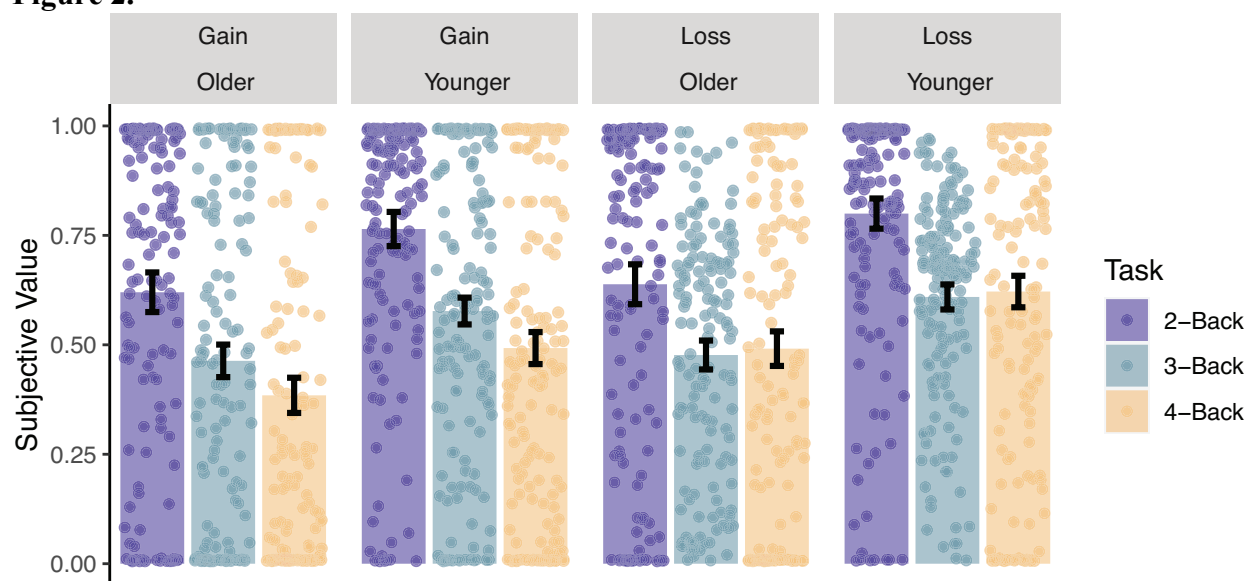| Predictors	Mental Demand Rating				Mental Demand Rating (YAs)				Mental Demand Rating (OAs)			
	Estimates	*CI*	*Statistic*	*p*	*Estimates*	*CI*	*Statistic*	*p*	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	2.13	2.04 – 2.22	45.89	**<0.001**	2.13	2.02 – 2.23	39.24	**<0.001**	1.99	1.90 – 2.07	44.52	**<0.001**
Age Group	-0.14	-0.26 – -0.02	-2.24	**0.025**								
Day of Week	-0.05	-0.06 – -0.04	-9.56	**<0.001**	-0.05	-0.07 – -0.03	-5.73	**<0.001**	-0.05	-0.07 – -0.04	-7.77	**<0.001**
Time of Day	-0.03	-0.06 – 0.00	-2.26	**0.024**	0.03	-0.02 – 0.08	1.27	0.204	-0.09	-0.12 – -0.05	-4.56	**<0.001**
SV (Gain)	0.75	0.42 – 1.09	4.38	**<0.001**	0.76	0.39 – 1.11	4.02	**<0.001**	0.27	0.01 – 0.52	2.06	**0.040**
SV (Loss)	-1.01	-1.39 – -0.63	-5.19	**<0.001**	-1.01	-1.42 – -0.59	-4.72	**<0.001**	-0.32	-0.59 – -0.05	-2.35	**0.019**
Age Group * SV (Gain)	-0.49	-0.93 – -0.05	-2.16	**0.030**								
Age Group * SV (Loss)	0.70	0.21 – 1.18	2.81	**0.005**								

Note. SV refers to the subjective value estimates across both the gain and loss incentive framing conditions. The results from the full model (first column) are broken down into the results for only younger adults (YAs; column two) and older adults (OAs; column three).
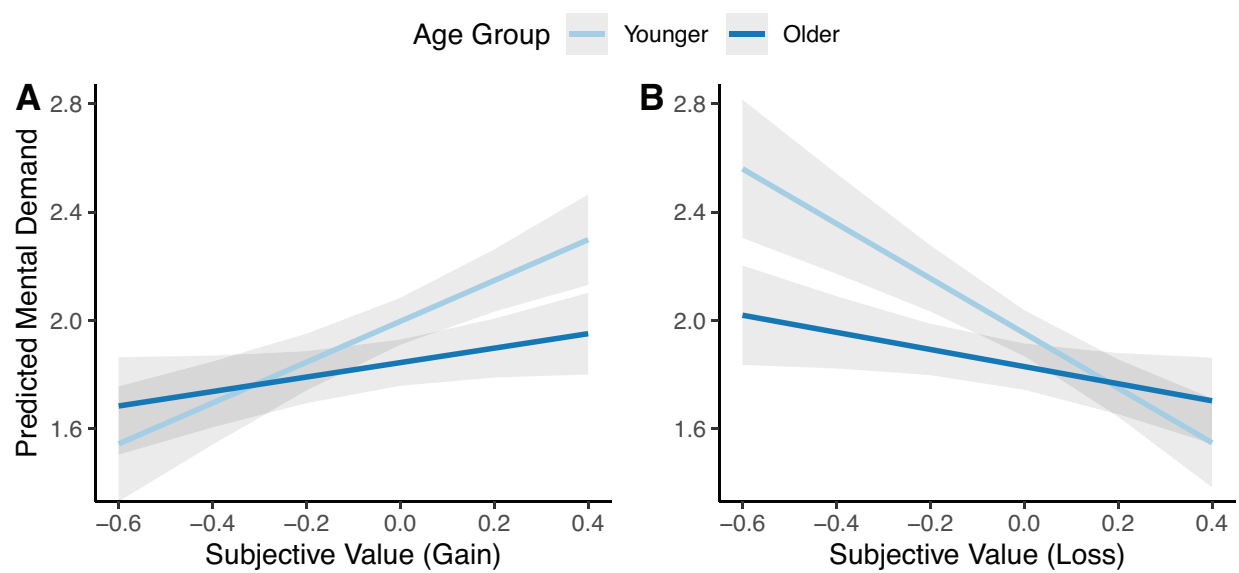
Figure 1.

A) Familiarization Phase

1-Back   *2-Back*   *3-Back*   *4-Back*

B) Discounting Phase

Gain

| $1.00 black | $2.00 red | | $2.00 red | $1.50 black | | $1.25 black | $2.00 red | | $1.38 black | $2.00 red | *indifference point* |

Loss

| -$2.00 black | -$1.00 blue | | -$1.00 blue | -$1.50 black | | -$1.00 blue | -$1.75 black | | -$1.88 black | -$1.00 blue | *indifference point* |

C) Performance Phase

Participant performs choice on <u>*randomly selected trial*</u> *from each phase of discounting*

-$1.50 black + $2.00 red = **$5.50 bonus payment**

Figure 2.

Figure 3.

Table and Figure Captions

Table 1. Effects of task level, incentive framing condition, age group, and task order on subjective value estimates (i.e., costs of cognitive effort).

Table 2. Results from the multilevel model of daily life mental demand with age group, time of day, day of week, and averaged gain and loss subjective value estimates as predictors.

Figure 1. Overview of the Cognitive Effort Discounting Paradigm (Cog-ED). A) Participants complete an initial familiarization phase where they perform 4-levels of the N-Back task in which they determine if the current letter is a target (bolded for visualization) or non-target. The color of the arrow for each task level corresponds to the label that level of the task is given to avoid anchoring effects (e.g., 2-Back = "red"). B) After task familiarization, participants complete the discounting phase during which they make a series of decisions about whether to repeat performance of a higher load-level of the task or instead perform the easiest load level. The offer amount for the lower effort option is stepwise titrated until the indifference point is reached. C) A trial from the discounting phase is selected (highlighted in orange) and participants complete that level of the task for the amount of money offered. Two trials are chosen in this experiment for participants to repeat: one from the gain discounting and one from the loss discounting.

Figure 2. Subjective value of cognitive effort predicted by age group, task level, and incentive framing condition. Higher values of subjective value signify lower costs of cognitive effort. Error bars represent 95% confidence intervals.

Figure 3. Daily life mental demand as predicted by gain and loss subjective value estimates across both younger and older adults (from multilevel model). Confidence bands represent 95% confidence intervals.