

Increased Cognitive Effort Costs in Healthy Aging and Preclinical Alzheimer's Disease

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Life-long engagement in cognitively demanding activities may mitigate against declines in cognitive ability observed in healthy or pathological aging. However, the “mental costs” associated with completing cognitive tasks also increase with age and may be partly attributed to increases in preclinical levels of Alzheimer's disease (AD) pathology, specifically amyloid. We test whether cognitive effort costs increase in a domain-general manner among older adults, and further, whether such age-related increases in cognitive effort costs are associated with working memory (WM) capacity or amyloid burden, a signature pathology of AD. In two experiments, we administered a behavioral measure of cognitive effort costs (cognitive effort discounting) to a sample of older adults recruited from online sources (Experiment 1) or from ongoing longitudinal studies of aging and dementia (Experiment 2). Experiment 1 compared age-related differences in cognitive effort costs across two domains, WM and speech comprehension. Experiment 2 compared cognitive effort costs between a group of participants who were rated positive for amyloid relative to those with no evidence of amyloid. Results showed age-related increases in cognitive effort costs were evident in both domains. Cost estimates were highly correlated between the WM and speech comprehension tasks but did not correlate with WM capacity. In addition, older adults who were amyloid positive had higher cognitive effort costs than those who were amyloid negative. Cognitive effort costs may index a domain-general trait that consistently increases in aging. Differences in cognitive effort costs associated with amyloid burden suggest a potential neurobiological mechanism for age-related differences.

Public Significance Statement

The cognitive costs associated with completing difficult mental tasks increases for older adults. Such increased costs may be related to the development of pathology associated with Alzheimer's disease. The present study findings contribute to our understanding of how older adults make decisions regarding the trade-off between the cost of expending cognitive effort and the value of rewards obtained from such effort, which may have important implications for daily life.

Keywords: aging, cognitive effort, Alzheimer's disease, amyloid

Supplemental materials: <https://doi.org/10.1037/pag0000742.supp>

This article was published Online First April 17, 2023.

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This research was supported by grants from the National Institute on Aging (NIA) awarded to John C. Morris (P30-AG066444, P01-AG03991, and P01-AG26276), to Andrew J. Aschenbrenner (Pilot 36.1 on NIA Grant P50-AG05681), to Todd S. Braver and Jonathan E. Peelle (R21-AG067295), an Alzheimer's Association research fellowship awarded to Andrew J. Aschenbrenner (2019-AARF-643898). Jennifer L. Crawford was supported by a training grant from the National Institute of Neurological Disorders and Stroke (T32-NS115672). Additional data collection was facilitated by NIA Grant R24-AG054355.

Anne M. Fagan has received research funding from the NIA of the National Institutes of Health, Biogen, Centene, Fujirebio, and Roche Diagnostics. She is a member of the scientific advisory boards for Roche Diagnostics, Genentech,

and Diadem and also consults for DiamiR and Siemens Healthcare Diagnostics Inc. Jason Hassenstab is a paid consultant or advisory board member for Roche, Lundbeck, and Paragon Nanolabs and is on the Data Safety and Monitoring Board for Eisai. Tammie L. S. Benzinger has served as a consultant and advisory board member to Eisai, Roche, and Lilly and has had research support from Avid Radiopharmaceuticals and Siemens. The authors have no conflicts of interest to disclose.

Data and analysis files for Experiments 1 and 2 can be found at https://osf.io/5kzan/?view_only=3b70069edafa429a81036e4527ce121f (Aschenbrenner et al., 2022a), and the preregistration document for Experiment 1 is available at <https://doi.org/10.17605/OSF.IO/M2G4B> (Aschenbrenner et al., 2021). A preprint of this article (Aschenbrenner et al., 2022b) has been posted to PsyArXiv (<https://doi.org/10.31234/osf.io/pfz6e>).

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Although it is well-established that aging is associated with decrements in a variety of cognitive functions (Park et al., 2002), individual trajectories of cognitive change are quite heterogeneous (Goh et al., 2012; Lindenberger, 2014). A major aim of cognitive aging research is to identify any individual difference factors that might contribute to variation in cognitive outcomes and promote successful aging in late life. One such factor that has received considerable attention in the literature is the life-long engagement in cognitively demanding or mentally stimulating activities. Greater or more frequent engagement in stimulating activity may attenuate the magnitude of age-related cognitive decline (Hultsch et al., 1999), protect against cognitive disruptions due to dementing illness (Stern, 2012), buffer against accumulation of pathology that contributes to Alzheimer's disease (AD; Landau et al., 2012), and reduce the risk of developing dementia (Wilson et al., 2002); however, it should be noted that these views are not universally accepted (Salthouse et al., 2002). At the same time, numerous studies have also converged on the notion that the very act of engaging in cognitive activity becomes more mentally "costly" with age. This is evidenced, for example, by increases in self-reported cognitive effort (Bunce & Sisa, 2002), behavioral indicators of cost via discounting paradigms (McLaughlin et al., 2021; Westbrook et al., 2013), dual task performance (Verhaeghen et al., 2003), or physiological markers such as systolic blood pressure (Hess & Ennis, 2014) and pupillometry (Piquado et al., 2010).

Along the same lines, a related literature has emerged which suggests that as individuals' age, they become more selective regarding the types of cognitive interactions in which they partake. Such enhanced cognitive selectivity might reflect a variety of motivational factors (Baltes & Baltes, 1990; Ennis et al., 2013; Hess, Freund, & Tobler, 2021; Swirsky & Spaniol, 2019). For example, the selection, optimization, and compensation (SOC) framework of successful aging by Baltes and Baltes (1990) explicitly suggests that individuals restrict (selection) activities to domains that are of high personal priority and those that enrich their lives in some fashion (optimization), due to the availability of specific resources (e.g., free time, cognitive abilities) that may limit achievement of specific goals. Given this framework, it is easy to conceive of a cost-benefit analysis whereby if the perceived cost of engaging in a cognitive activity (indexed either by psychological factors such as mental fatigue or other considerations such as time spent on the task) outweighs the perceived benefits (emotional fulfillment, protection against cognitive decline), individuals may then choose not to participate in that activity. Therefore, to encourage and promote successful aging, it is of critical interest to identify the specific mechanisms that contribute to engagement in cognitive activity, and whether these mechanisms are task-specific or domain-general.

Assessing Cognitive Effort

Investigation of age-related differences in cognitive effort and cost requires such constructs to be rigorously defined. We adopt an operational framework inspired by Westbrook and Braver (2015) who broadly defined effort as the degree or amount of engagement with a given activity. Although effort can be devoted to any number of activities (e.g., physical activity, social activity), in the present study we focus exclusively on cognitive effort: that is, effort devoted to a cognitive or mental activity. Moreover, effort can be measured in absolute terms (e.g., by asking "how much effort did you expend

on this test?") but it is often more useful to index effort in terms of "costs," that is, the change in behavior, performance or self-ratings observed when comparing an easier task or condition to a more difficult task or condition. Even with these operational definitions, the assessment of the cognitive effort and costs is nontrivial; as such, there are a variety of outcomes to measure it, each of which affords certain advantages and disadvantages. Physiological variables such as pupillometry (Laeng et al., 2012) or blood pressure (Hess & Ennis, 2014) are useful as measures of exerted effort but do not assess participant preferences or choice behavior regarding engagement. Several subjective, questionnaire-based metrics of cognitive effort (e.g., the NASA Task Load Index, Hart & Staveland, 1988) and preferences regarding engaging in stimulating or demanding cognitive activity (the Need for Cognition Scale, Cacioppo & Petty, 1982) exist, but both are potentially vulnerable to the well-known biases associated with subjective reports.

Behavioral tasks have been developed to measure cognitive effort costs without requiring explicit subjective reports. For example, the demand selection task (Kool et al., 2010) requires participants to select between two visual patterns that are differentially associated with a relatively hard versus a relatively easy task. The degree of preference for the easy task is taken as an index of avoidance of effortful activity. Of course, task difficulty is only one parameter in the cost-benefit equation that indicates whether it is advantageous to engage in effortful activity. Another parameter is the amount of expected reward, which is not manipulated in tasks such as demand selection. Westbrook et al. (2013) developed the cognitive effort discounting task (COG-ED), which relies on the principle of discounting and infers participants' preferences based on choice behavior regarding task engagement using a staircase procedure to determine the amount of reward that an individual will accept to engage with a given task. For example, Westbrook et al. (2013) administered the *N*-back which parametrically increased in difficulty. After familiarizing participants with each task level so that they would be able to estimate the effort associated with performance, participants entered a discounting phase in which they had to choose between completing a more difficult task for a larger reward or an easier task for a smaller reward. Offered rewards are titrated until an indifference point is reached, the point at which the harder and easier tasks are equally preferred for the given reward. As a simple example, if an individual equally prefers the easier Task A for \$1.00 or the more difficult Task B for \$2.00, then the "subjective value" (SV) of the higher reward is 0.5, meaning the participant is willing to forgo 50% of the value of the high-effort, high-reward task to instead perform the low-effort task. This SV metric is then used as an indicator of cognitive effort cost, in that it incorporates the trade-off between reward optimization (in this case monetary value) and estimates of cognitive difficulty (i.e., task load). Westbrook et al. (2013) originally validated the task by showing that SVs decrease across age and task load and that such effects cannot be explained based on observed task performance during the familiarization phase. A potential disadvantage of the COG-ED is that it does not assess exerted effort directly but rather participant's explicit preferences regarding engagement with various levels of cognitive activity. As we are principally interested in decisions regarding cognitive effort engagement, we utilize the COG-ED in the present study.

Importantly, the COG-ED has now been validated in multiple studies. Repeated administrations of the task have demonstrated some stability in COG-ED measures over time (ICC = 0.48,

Westbrook et al., 2019). Moreover, there are similarities between COG-ED and standard delay-discounting paradigms, in that both are typically utilized to estimate the trade-offs between reward-related benefits and a particular cost, such as delay, risk, or effort (Białaszek et al., 2019; Seaman et al., 2016). However, prior work with the COG-ED suggests that it may tap into unique mechanisms that are distinct from other forms of discounting, such as delay (Westbrook et al., 2013). SVs have been reported to be lower in older adults (Hess, Lothary, et al., 2021; McLaughlin et al., 2021; Westbrook et al., 2013), are lower in individuals with negative affect symptoms such as schizophrenia (A. Culbreth et al., 2016), and correlate with functional magnetic resonance imaging blood oxygen level dependent signal in critical brain regions and functional networks such as the valuation network which includes important regions such as the ventral medial prefrontal cortex, and the posterior and anterior cingulate cortex (Culbreth et al., 2020; Westbrook et al., 2019). The sensitivity of COG-ED SVs to a variety of important individual characteristics points to the reliability of the task as a measure of effortful engagement.

Mechanisms of Age-Related Differences in Cognitive Effort Costs

Although behavioral assessments of cognitive effort costs are arguably more objective than simple questionnaires, expenditure of cognitive effort is ultimately a decision based, at least in part, on subjective experience. That is, individuals *choose* to exert cognitive effort based on their perceptions of a variety of factors including how difficult the task is and the magnitude and relevance of associated rewards that are on offer. The decision to engage in effortful activity is likely associated with a number of mechanisms including motivation, goal-optimization, self-efficacy, reward sensitivity, or cognitive control, all of which are overlapping, but not redundant with, cognitive effort (Westbrook & Braver, 2015). The overarching goal of the present study was to identify and evaluate several critical individual factors that might contribute to age differences in cognitive effort costs.

As already mentioned, one explanation of increasing cognitive costs with age is an associated decline in general cognitive ability; or relatedly, a decline in sensory ability (such as hearing) that may increase cognitive demands (Peelle, 2018; Peelle & Wingfield, 2016). For example, Tun et al. (2009) showed that declines in hearing ability accounted for increased dual task cost in a listening task. Westbrook et al. (2013) showed that performance in an ongoing working memory (WM) task partially accounted for variance in cognitive effort costs, while McLaughlin et al. (2021) also demonstrated that both hearing ability and WM capacity accounted for age-related variance in a cognitive effort costs during an effortful listening paradigm. Considering both of these studies, it can be proposed that older adults have higher perceived cognitive effort costs simply because they typically have overall lower WM capacity and worse sensory capabilities than younger adults. However, it should be noted that at least one study using self-report measures of effort showed no correlation between effort and WM capacity (Brose et al., 2010), so the WM—cognitive effort relationship certainly merits additional investigation.

In terms of neurobiological mechanisms, valuations of cost and effort have been linked to specific brain regions and systems, including the ventromedial prefrontal cortex and striatum (Lopez-Gamundi et al., 2021; Westbrook et al., 2019), midbrain dopamine systems (Froböse et al., 2020; Westbrook & Braver, 2016; Westbrook

et al., 2020), and the default mode network (Barnes et al., 2009; see Westbrook & Braver, 2015 for a full review). Here, we explore another possibility: that increases in amyloid pathology are associated with age-related differences in cognitive effort costs. The accumulation of amyloid plaques is one of the hallmark pathological signatures of AD, a highly prevalent and progressive neurodegenerative disorder that also includes neurofibrillary tangles of the protein τ , both of which lead to neuronal atrophy, loss of function, and ultimately death. Pathology of AD can accumulate for decades before clinical symptoms of dementia become apparent (Bateman et al., 2012; Price et al., 2009), with pathology prevalence rates in a clinically healthy population estimated at 17% for amyloid and 18% for τ at age 65. These estimates increase to 54% for amyloid and 42% for τ at age 80 (Jack et al., 2017). Thus, a relatively large proportion of any purportedly healthy older adult sample will likely have a clinically relevant amount of AD pathology and inclusion of these participants in studies on “healthy” cognitive aging may bias estimates of cognitive trajectories (Harrington et al., 2021). Critically, as we suggest here, the otherwise undetected AD pathology may also impact estimates of cognitive effort costs. Indeed, amyloid tends to accumulate in the prefrontal cortex and other regions associated with the default mode network (Buckner et al., 2005; Mintun et al., 2006), and mouse models suggest that there may be a relationship between amyloid and dopamine transmission (Moreno-Castilla et al., 2016). The overlap between brain regions (and neurotransmitters such as dopamine) associated with the computation of cognitive effort cost and amyloid accumulation suggest that a relationship may exist between the two.

The relationship between cognitive effort cost and amyloid accumulation has been most explicitly postulated in the waste management hypothesis (Holroyd, 2016). In this theoretical account, the engagement of cognitive effort specifically produces amyloid- β peptides, and the nervous system aims to clear these peptides as quickly as possible. A rapid accumulation of amyloid therefore produces feelings of fatigue, which may lead to increased cognitive effort costs and reduced activity participation enabling the system to “catch-up” via additional clearance of amyloid. This theory has been supported by mouse models demonstrating that increased synaptic activity increases levels of amyloid β in the interstitial fluid (Cirrito et al., 2005), which is then cleared out during periods of inactivity, especially during sleep (Xie et al., 2013). Additionally, it is known that amyloid β clearance is impaired in AD (Mawuenyega et al., 2010), leading to the accumulation of amyloid plaques that is the pathological signature of the disease. Bringing these various ideas together, we propose that engaging in a cognitively difficult activity leads to the production of amyloid, which for many older adults may not be efficiently removed, leading to higher perceived cognitive effort costs and ultimately a preference to not engage with such activities.

Are Cognitive Effort Costs Domain-General or Task-Specific?

One unanswered question is whether cognitive effort costs index a domain-general, trait like construct (i.e., a preference to avoid cognitively demanding activity) as opposed to a task-specific phenomenon (i.e., I find this task difficult, therefore I will avoid it). There is some evidence to suggest that WM capacity is at least partially responsible for age differences in effort costs (McLaughlin et al., 2021; Westbrook et al., 2013). This makes sense from the view

that WM capacity indexes the functioning of a central executive process responsible for initiating goal-directed behavior, maintaining and retrieving task goals and representations, and directing attention (Baddeley & Hitch, 1974). Furthermore, it is well-established that increasing age is associated with declines in WM capacity (Bopp & Verhaeghen, 2005). To the extent that correlations between effort cost and cognitive ability rely on a single task or cognitive domain, it remains unclear whether such relationships arise because the ongoing task specifically taps WM or because an overall reduction in capacity leads to a domain-general increase in cognitive cost.

Studies using innovative methods of measuring cognitive effort costs have provided some support for a domain-general cognitive effort construct. Crawford et al. (2022) administered the COG-ED paradigm to a sample of younger adults using two different cognitive tasks, the *N*-back to measure WM, and a comprehension of speech-in-noise task. Cognitive effort cost estimates from both domains were significantly correlated. Similarly, Strobel et al. (2020) showed that demand avoidance, another indicator of cognitive cost, was correlated across a magnitude determination task and a consonant/vowel decision task. Importantly, however, neither of these studies examined performance in an older adult sample in which variations in task performance and WM capacity are likely to be much greater.

Study Aims

The primary aim of the present study was to examine cognitive and neurobiological mechanisms that underlie age differences in cognitive effort costs. We achieve this aim by testing three specific hypotheses across two independent studies. First, in Experiment 1, we hypothesized that the cognitive effort costs reflect a stable and domain-general individual difference variable among older adults. If age-related increases in cognitive effort costs are due to a single underlying mechanism (e.g., reduced mental resources, impaired amyloid clearance) then effort costs would be expected to be similar across disparate cognitive domains. Prior work has found age differences in cognitive effort costs in using both an *N*-back test (Westbrook et al., 2013) and a speech comprehension task (McLaughlin et al., 2021). In the present study, we examine both

versions in a within-subjects design, allowing us to test for age-related differences in domain-general cognitive effort costs.

Second, we hypothesize that the age-related differences in WM capacity may serve as a mechanistic explanation for age-related increases in cognitive effort costs. We test this idea by correlating cognitive effort cost estimates with a composite WM capacity score. We also examine whether the extent to which cognitive effort costs from COG-ED are associated trait measures of effortful engagement using the Need for Cognition Scale (Cacioppo & Petty, 1982).

Finally, in Experiment 2, we hypothesize that the age-related differences in cognitive effort costs are at least partially due to pathological accumulation of amyloid β . We administered a version of the COG-ED paradigm to a sample of participants enrolled in ongoing longitudinal studies of memory and aging at the Knight Alzheimer Disease Research Center (ADRC). We hypothesized that individuals with elevated levels of preclinical amyloid pathology would express lower SVs (increased cognitive effort costs) relative to those without abnormal pathology. Moreover, we hypothesized that the behavioral COG-ED measure would outperform questionnaire-based metrics of effort or engagement (e.g., NASA Task Load Index and the Need for Cognition Scale, see Table 1) in terms of providing sensitivity to pathology. That is, we expected the influence of amyloid pathology would be more apparent on the COG-ED measures of effort costs due to the advantages afforded by a more sensitive behavioral measure. It is important to note that we are not advocating for the use of effort discounting as a diagnostic tool of preclinical AD, but rather testing the notion that increased amyloid burden will be correlated with increased effort costs. Thus, we do not compare performance of the COG-ED in identifying amyloid pathology compared to standard clinical instruments such as the Montreal Cognitive Assessment (Nasreddine et al., 2005).

Experiment 1

Method

Transparency and Openness

This study was preregistered; however, we extended the statistical analysis to utilize Bayesian mixed-effects models rather than repeated

Table 1
Group Performance on All Test Scales in Experiments 1 and 2

Variable	Experiment 1		Experiment 2	
	Younger	Older	Amyloid negative	Amyloid positive
Need for cognition	60.5 (16.2)	66.2 (14.5)	63.1 (11.9)	62.0 (12.7)
NASA effort working memory				
1-back	10.7 (5.4)	10.7 (5.5)	9.4 (4.8)	9.0 (4.7)
2-back	13.7 (4.5)	13.5 (5.1)	12.8 (4.0)	13.0 (4.6)
3-back	16.0 (3.9)	15.4 (4.6)	14.7 (3.2)	14.3 (5.5)
4-back	17.2 (3.6)	16.3 (4.7)	16.0 (3.1)	14.5 (5.9)
NASA effort speech				
0 SNR	12.9 (5.0)	12.8 (4.9)	NA	NA
-4 SNR	15.2 (4.4)	15.5 (4.3)	NA	NA
-8 SNR	17.5 (3.6)	17.5 (3.8)	NA	NA
-12 SNR	18.5 (3.4)	18.5 (4.2)	NA	NA
Listening span	43.2 (12.1)	41.9 (11.9)	NA	NA
Symmetry span	20.5 (10.3)	10.6 (7.6)	NA	NA
Operation span	48.8 (18.3)	43.0 (19.6)	NA	NA

Note. Continuous variables are presented as means (standard deviations), and categorical variables are represented as percentages. Data from the younger adult sample in Experiment 1 were taken from Crawford et al. (2022). SNR = signal-to-noise ratio; NA = not applicable.

measures analysis of variances. All analysis scripts and data files are available at Open Science Framework. This project (Multi-domain Discounting, Protocol No. 201909202) was approved by the Institutional Review Board at Washington University in St. Louis.

Participants

We enrolled a sample of older adult participants in a multiday online experiment that was designed to examine COG-ED performance in relation to a battery of individual difference measures including WM capacity and reward sensitivity. This experimental protocol was specifically designed to be identical to Crawford et al. (2022) to afford age-related comparisons with their sample of younger adult participants. The online recruitment platform <https://Prolific.co> (Palan & Schitter, 2018) was used to identify potential research participants, with the following inclusion criteria: at least 60 years of age,¹ a native speaker of English, and having no self-reported hearing difficulties. Data collection was restricted to individuals residing in the United States to avoid differences across types of currency. The first participant enrolled July 14, 2021, and data collection ended on October 12, 2021. This study was preregistered on Open Science Framework and we originally aimed to enroll 100 participants, which is similar to the sample size enrolled by Crawford et al. (2022) and would allow us to detect a group difference in SV ratings between younger and older adults of a moderate effect size (Cohen's $D = 0.5$) with approximately 94% power.

Ultimately, a total of 128 individuals initially consented to participate; however, due to technical issues in getting audio stimuli to play on certain individual's computers only 87 participants returned on Day 2 to complete all COG-ED procedures. Of those 87, 13 participants reported not using headphones during the speech comprehension task as instructed, and thus were removed leaving a total of 74 older adult participants available for analysis ($M_{\text{age}} = 64.9$, $SD_{\text{age}} = 3.9$, 62% female, 67 participants reported their race as White, four as Black or African American, one as Asian, and two as more than one race). Note that this sample size is considerably larger than those collected in prior studies (e.g., $N = 30$ and 16 in Experiments 1 and 2, respectively, in Westbrook et al., 2013; $N = 50$ in McLaughlin et al., 2021). This sample of older adults was then compared to a previously collected sample of 104 younger adults ($M_{\text{age}} = 27.3$, $SD_{\text{age}} = 5.8$, 45% female) who underwent the same battery of tests (Crawford et al., 2022).

Task and Measures

The experiment occurred over 2 days. On Day 1, participants completed a WM capacity battery that consisted of listening span (Cai et al., 2015), symmetry span, and operation span (Unsworth et al., 2005). They also completed the Need for Cognition Scale to assess trait levels of cognitive engagement (Cacioppo & Petty, 1982), which is an 18-item questionnaire where participants rate statements such as "I prefer complex to simple problems on a 5-point scale from *extremely uncharacteristic of me* to *extremely characteristic of me*. Scores were summed across items to form a mean Need for Cognition score where higher values indicate more likely to seek out and enjoy cognitively demanding activities.

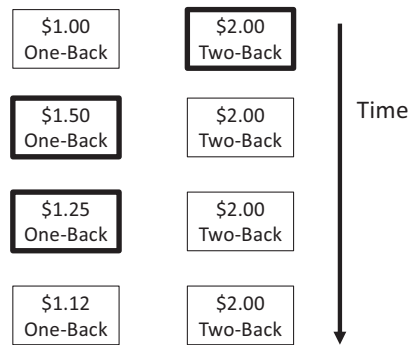
On the second day, participants completed two different versions of the COG-ED task in a fixed order. Both versions consisted of two different phases. A familiarization phase, in which participants

completed four blocks of a cognitive task with each block increasing in objective difficulty. The two versions of COG-ED differed in the cognitive task used in this phase. In the WM COG-ED task, participants completed the N -back task. In the N -back task, letters are shown on the screen one at a time and participants are asked to indicate if the current letter matches the letter that was displayed " N " trials ago. For example, in the 1-back task participants would determine if the current letter matched the previous letter. Participants completed four blocks of the N -back with increasing difficulty (1-back, 2-back, 3-back, and 4-back) and each block consisted of 20 trials (five targets and 15 nontargets). In the speech-in-noise COG-ED, participants listened to spoken sentences and were asked to type the sentence that they heard. Difficulty was increased across blocks by adding increasing levels of background noise to the speech signal (i.e., decreasing the signal-to-noise ratio [SNR]). For example, an SNR of -12 dB would indicate the noise was 12 dB louder than the signal. Four blocks were completed at SNRs of 0, -4 , -8 , and -12 dB, with each block consisting of 15 trials. After completing each level of task difficulty in the familiarization phase, participants were given feedback on the number of items they got correct and then they completed ratings from the NASA Task Load Index to index self-reported mental demand, effort, frustration, and performance of each load level using a rating scale ranging from 1 (*very low*) to 21 (*very high*).

Immediately after the familiarization phase for a given task, participants entered the discounting phase. Here, participants were asked if they would like to repeat a higher level of the task (e.g., 4-back or -12 dB SNR) or the easiest level of the task (1-back or 0 dB SNR) for a given amount of reward. Each of the three higher levels (2-back, 3-back, 4-back, or -4 dB SNR, -8 dB SNR and -12 dB SNR) was always paired with the easiest version of the task. For the first presentation of each difficulty pair, the offered reward amount was always the same (e.g., would you prefer to complete the 2-back again for \$2.00 or the 1-back again for \$2.00). The offered rewards were then step-wise titrated until an indifference point was reached. The reward amount that was titrated depended on the initial selection. That is, if the participant selected the 1-back for \$2.00 over the 2-back, the reward amount for the lower effort task was titrated (reduced by half) whereas if the participant selected the 2-back, the higher effort task was titrated until the indifference point was reached. The indifference point is normalized to the higher reward amount to create an SV which is taken as the estimate of cognitive cost of that task and values of >1 indicated that participants preferred to forgo money in order to attempt more difficult levels of the task. Participants made six effort decisions with base rewards of \$2, \$3, and \$4 for a total of 18 discounting choices per level of difficulty. SVs were averaged across the different base reward amounts. A simplified illustration of the discounting portion of COG-ED is provided in Figure 1. Participants did not actually receive the stated rewards from every trial. Instead, a standard approach from neuroeconomics was implemented, in which participants were instructed that one of their choices (e.g., \$2 for the 2-back) would be repeated at the end of

¹ Participants age is collected by <https://Prolific.co> but also by our demographics questionnaire. One participant reported being above the age limit for <https://Prolific.co> but was listed as age 55 on our demographics questionnaire. Without being able to determine if this was a typo or deliberate misrepresentation of their age, we opted to leave the participant in the analysis.

Figure 1
Simplified Illustration of the Discounting Portion of the COG-ED Task



$$SV = 1.12 / 2.00 = 0.56$$

Note. Thick lines indicate the choice made by the participant. COG-ED = cognitive effort discounting; SV = subjective value.

the task. Thus, each trial was incentivized, in the sense that it could be the one that is randomly chosen to repeat (for actual money) at the end of the task; however, participants were not rewarded with money from each and every decision. The “bonus” from the randomly chosen trial was in addition to the flat reimbursement fee (\$20) awarded for participating in the study as a whole. Moreover, participants were told that they would receive the amount of money selected on that choice, if they could maintain the same level of effort expended during the familiarization task, but “level of effort” was not evaluated in reference to any metrics from the familiarization task. The average bonus payment across all participants in the study was $\$1.96 \pm \1.31 for the WM COG-ED and $\$1.76 \pm \1.37 for the speech COG-ED. As a metric of reliability (i.e., internal consistency of between-person variability), we estimated intraclass correlations (ICCs) from a linear mixed-effects model separately for each age group. The obtained ICCs were 0.18 for younger adults and 0.52 for older adults.

Statistical Analysis

Average SVs for each difficulty condition and cognitive domain were analyzed using a Bayesian mixed-effects model using the brms package (Bürkner, 2018) and correlation analyses were conducted using the correlation package (Makowski et al., 2020) in R Version 4.0.5 (R Core Team, 2021). Fixed effects included “difficulty” (2-back, 3-back, or 4-back for the WM task and -4, -8, and -12 SNR for the speech task), Domain (WM vs. Speech), and age group (younger vs. older). The effect of difficulty was modeled as a linear trend and the other factors were entered as dummy codes (reference groups = Older adults and speech task). SVs were modeled with a student's *t* distribution to allow for heavy tails and prior distributions were designed to be relatively wide. Details on model fitting and convergence statistics are provided in the Supplemental Materials. Results are reported as the mean estimate of the posterior with a 95% credible interval (CI), rounded to two decimal places. An effect with an associated CI that excludes zero can be considered statistically significant. Bayes factors (BFs) are frequently also provided and interpreted

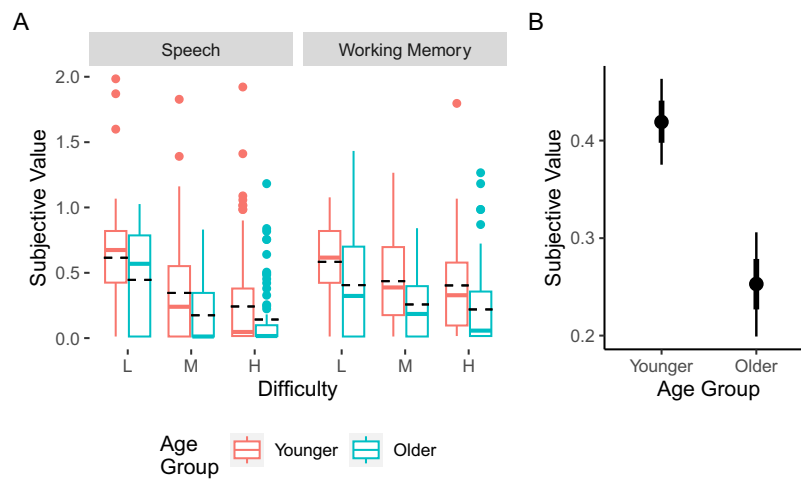
as the weight of evidence for a model, specifically, models in which the parameter in question is freely estimated versus one in which it is assumed to be zero. However, BFs depend heavily on the prior distributions that are specified and test the fitted model against a very specific alternative, one in which the parameter of interest is exactly zero, akin to null hypothesis significance testing. Consequently, we chose not to calculate BFs but rely exclusively on mean parameter estimates and CIs to determine the relative importance of a particular parameter. Within-domain analyses were conducted while controlling for performance in the familiarization task to ensure cost estimates are not confounded with task performance. Finally, average SV estimates within a domain were correlated with a WM composite score (a *z* scored average of the three WM tests) and the total score of the Need For Cognition Scale, in order to evaluate the extent to which cognitive costs are related to total ability/capacity and self-reports of effortful engagement.

Results

Mean SV estimates are plotted as a function of age group, domain, and difficulty condition in Panel A of Figure 2. The linear contrast of difficulty condition was significant ($\beta = -0.19$, CI [-0.24, -0.13]), indicating that SVs decreased as task load increased, as expected from many prior studies. The main effect of domain was not significant ($\beta = 0.04$, CI [-0.00, 0.08]). Finally, the main effect of age group was significant ($\beta = 0.14$, CI [0.07, 0.22]), indicating that younger adults endorsed higher SVs than older adults regardless of domain (see Panel B of Figure 2). There was a small interaction between difficulty and domain ($\beta = 0.08$, CI [0.00, 0.15]), indicating that discounting was slightly steeper in the speech task. There was an age by difficulty interaction ($\beta = -0.09$, CI [-0.16, -0.02]) indicating that discounting across task load was slightly steeper for the younger as compared to the older adults. Neither the age by domain ($\beta = 0.05$, CI [-0.00, 0.11]) nor the three-way interaction among difficulty, domain and age were significant ($\beta = 0.05$, CI [-0.05, 0.14]). Follow-up tests within domain confirmed significant age effects were present in both the WM task ($\beta = 0.19$, CI [0.12, 0.27]) and speech task ($\beta = 0.14$, CI [0.07, 0.22]). Conditional model plots of the age effect within domain are presented in the Supplemental Materials.

Additional analyses conducted within cognitive domain and controlling for performance in the familiarization task again yielded a significant age effect in both WM ($\beta = 0.18$, CI [0.10, 0.26]) and speech comprehension ($\beta = 0.15$, CI [0.06, 0.23]), indicating that age differences in effort discounting are not due to age differences in performance in the primary tasks. The correlation between average SV (across all difficulty levels) in the WM domain and average SV in the speech domain (across all difficulty levels) was significant for the older adults (Figure 3: $r = 0.56$, CI [0.40, 0.70]), which is noticeably and statistically larger than the correlation of 0.29 (CI [0.14, 0.42]) reported in the younger adults by Crawford et al. (2022) (Fischer *r*-to-*z* = 2.25, *p* value = .02). Among older adults, the WM span composite score was not correlated with SV in either the WM domain ($r = -0.02$, CI [-0.26, 0.18]) or the speech domain ($r = -0.13$, CI [-0.35, 0.08]). Finally, Need for Cognition did not correlate with SV in either domain (WM: $r = 0.09$, CI [-0.14, 0.28]; speech: $r = 0.16$, CI [-0.06, 0.35]). Scatterplots of these latter relationships are provided in Figure 4.

Figure 2
COG-ED Performance in Experiment 1



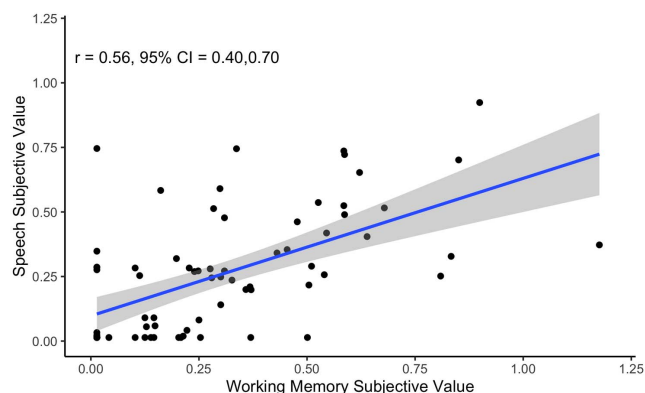
Note. Panel A: Boxplots of the average subjective values (SVs) for each age group, task, and difficulty level. Solid lines represent the medians and the dashed lines represent the mean. Panel B: Main effect of age group on SV in Experiment 1. COG-ED = cognitive effort discounting. See the online article for the color version of this figure.

Discussion

The results from Experiment 1 were very clear. Both versions of the COG-ED task showed that SV significantly decreases across task load. Thus, as the ongoing task becomes more difficult, perceived cognitive effort cost increases. More importantly, we replicated prior demonstrations of an age effect on SV (McLaughlin et al., 2021; Westbrook et al., 2013) in two different cognitive domains. Specifically, older adults report increased cognitive effort costs (lower SV) relative to younger adults. There was not much evidence for task differences across domains as SV estimates were not significantly different between the WM and speech comprehension tasks. Moreover, the magnitude of the age differences was also largely similar across the

two domains. Although discounting was steeper in the speech task compared to WM task, this effect did not interact with age group. Most importantly, the SV estimates across the two tasks were highly correlated suggesting the presence of a stable and domain-general cognitive effort cost construct. As a whole, these results point to the utility of using COG-ED as a marker of cognitive effort cost (as shown by decreasing SVs across load) and as an individual difference characteristic (in this case, age). Surprisingly, the relationship between SV estimates and overall capacity (WM) was rather small and not statistically significant, suggesting that age-related increases in cognitive effort cost cannot be explained by declines in a central executive ability. Moreover, the age-related differences in SV estimates remained even after statistically controlling for performance in the familiarization task. In other words, there was no evidence that the SV of performing a cognitively effortful task was related to how well that task was performed during the familiarization phase.

Figure 3
Relationship Between Working Memory SV and Speech SV, Collapsed Across All Difficulty Levels, in Experiment 1

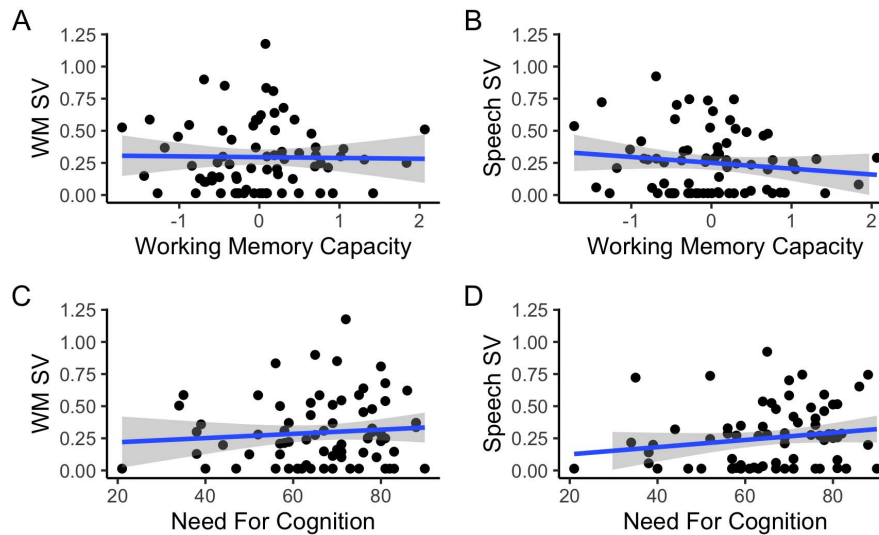


Note. SV = subjective value; CI = credible interval. See the online article for the color version of this figure.

Experiment 2

The results of Experiment 1, as well as converging evidence from other studies, clearly indicate that cognitive effort costs increase with age. As previously reviewed, many neurobiological explanations of this phenomenon have been proposed (e.g., dopamine transmission). Yet, one mechanism that has not been extensively tested is the waste management account (Holroyd, 2016) postulating amyloid as a key correlate of cognitive effort costs. Such a hypothesis is highly relevant to the study of cognitive aging since pathological amyloid accumulation is found in a relatively large proportion of otherwise healthy older adults. To our knowledge, the relationship between amyloid burden and cognitive effort costs have not been explicitly tested. Therefore, conducted independently of and in parallel to Experiment 1, Experiment 2 was designed to test the hypothesis that age-related increases in amyloid burden may be a potential neurobiological mechanism associated with increased

Figure 4
Correlations Between Cognitive Effort Cost and Working Memory Capacity (Top Panels) or Need for Cognition (Bottom Panels) in Experiment 1



Note. SV = subjective value; WM = working memory. See the online article for the color version of this figure.

cognitive effort costs observed on the COG-ED task among older adults.

Method

Transparency and Openness

Data and analysis scripts for this study are available on the Open Science Framework; however, this study was not preregistered. This project (Validating an Online Test to Assess Cognitive Effort in Alzheimer Disease, Protocol No. 201901211) was approved by the institutional review board at Washington University in St. Louis.

Participants

A total of 80 participants from the Knight ADRC at Washington University School of Medicine were enrolled to complete this study. Data collection began in December 2019 and ended in October 2020. The majority of participants from the Knight ADRC reside in or near the St. Louis metropolitan area; however, a few participants come from all areas of the geographic United States. We did not collect geographic information on our participants for this study. Based on a power analysis conducted with G*Power 3.1 (Faul et al., 2009), 80 participants would be sufficient to detect a moderate correlation ($r = 0.3$) with 80% power. Of the 80 individuals enrolled, four did not complete all study procedures. Furthermore, two participants had evidence of mild clinical impairment based on a clinical interview (described below) and four others had no in vivo biomarker assessments of amyloid within 5 years of completing the COG-ED task. These 10 participants were removed from analysis leaving a total of 70 participants. To maximize our sample size, as not all participants received all biomarker assessments, individuals were then split into amyloid “positive” or amyloid “negative”

groups based on established cutoffs (described below) on one or both of the amyloid biomarkers we had available. A total of 49 participants were amyloid negative (age: $M = 74.5$, $SD = 5.5$; education: $M = 16.8$ years, $SD = 2.2$; 61% female; 16% Apolipoprotein E (APOE) E4+²; 84% White and 16% African American) and 21 were amyloid positive (age: $M = 77.5$, $SD = 5.0$; education: $M = 17.1$ years, $SD = 1.9$; 62% female; 43% APOE E4+; 100% White and 0% African American).

Clinical Assessment

All participants at the Knight ADRC undergo a comprehensive clinical examination that includes the Clinical Dementia Rating (CDR) scale to rate the presence and, when present, the severity of dementia (Morris, 1993). The CDR uses a semistructured clinical interview to determine presence of impairment in six domains. These ratings are then synthesized into a global dementia rating where a score of 0 indicates cognitive normality; 0.5 indicates very mild dementia; and 1, 2, and 3 indicates mild, moderate, and severe dementia, respectively. Since our interest was on preclinical AD versus healthy aging, all participants in the present study were required to be rated as CDR 0.

Cerebrospinal Fluid Measurement

Cerebrospinal fluid (CSF) was collected under standardized operating procedures. Participants underwent lumbar puncture at approximately 8 a.m. following overnight fasting. About 20–30 mL

² One participant did not have APOE information available; to include them in the statistical models we used “mode imputation” and recorded this participant as APOE e4 negative. It should be noted that results change little if the participant was instead recorded as “APOE e4 positive” or even removed entirely from the sample.

of CSF was collected in a 50 mL polypropylene tube via gravity drip using an atraumatic Sprotte 22 gauge spinal needle. CSF was kept on ice and centrifuged at low speed within 2 hr of collection to pellet any cellular debris. CSF was then transferred to another 50 mL tube. CSF was aliquoted at 500 μ L into polypropylene tubes and stored at -80°C as previously described (Fagan et al., 2006). Prior to analysis, samples were brought to room temperature per manufacturer instructions. Samples were vortexed and transferred to polystyrene cuvettes for analysis. Concentrations of A β 40, A β 42, total τ (tTau), and τ phosphorylated at 181 (pTau) were measured by chemiluminescent enzyme immunoassay using a fully automated platform (LUMIPULSE G1200, Fujirebio, Malvern, Pennsylvania) according to manufacturer's specifications. A single lot of reagents were used for all samples. Samples were analyzed over 16 days. Internal pooled CSF controls were run 2–3 \times per day. Individuals were classified as amyloid positive if their ratio of A β 42 to A β 40 was less than 0.0673. This cutoff has shown to be very accurate in determining levels of amyloid pathology in the brain (Schindler et al., 2018).

Amyloid PET Imaging

Currently, two amyloid imaging tracers are used in our studies, that is, [^{11}C]-Pittsburgh Compound B (PiB) and [^{18}F]-Florbetapir (AV45). For both tracers, two modeling approaches are implemented: (a) binding potential (BP_{ND}) is calculated using Logan graphical analysis (Logan et al., 1996; Mintun et al., 2006; Su et al., 2013, 2015), when full dynamic Positron Emission Tomography (PET) imaging data are available, that is, PET acquisition was started in synchronization with tracer administration and PET images were reconstructed into multiple time frames; (b) regional target-to-reference intensity ratio, also known as, standard uptake ratio (SUV r), is estimated for all processable PET data. Under standard protocol, quantitative PET analysis (both BP_{ND} and SUV r) uses 30–60 min postinjection as the time window for PiB and 50–70 min for AV45; and the cerebellum cortex is used as the default reference region. To assess global amyloid burden based on amyloid PET imaging data, the arithmetic mean of BP_{ND} or SUV r s from precuneus (PREC), prefrontal cortex (PREF), gyrus rectus (GR), and lateral temporal (TEMP) regions are defined as the mean cortical binding potential (MCCBP) or mean cortical SUV r (MCSUV r). PET imaging analyses are performed using the PET unified pipeline (PUP; <https://github.com/ysu001/PUP> (Su et al., 2013, 2015)). To define amyloid positivity, we used internal SUV r cutoffs of 1.42 for PiB and 1.18 for AV45.

COG-ED Task

The N -back version of COG-ED was used in this experiment, since it has a longer and more well-established history in the literature (A. Culbreth et al., 2016; Froböse et al., 2020; Westbrook et al., 2013, 2019). The version used here was similar to but developed independently of the version adopted in Experiment 1. The primary differences were that participants completed 2.5 min each of the 1-back, 2-back, 3-back, and 4-back WM task, as opposed to a fixed number of trials as in Experiment 1. Second, in the discounting phase, we offered base amounts of \$1.00, \$2.00, \$5.00, and \$10.00, with each level of N -back always being compared to the 1-back as a reference. Again, higher SV ratings indicate lower subjective cognitive cost for completing the more difficult task. Participants

were told that the monetary values on offer were hypothetical but like Experiment 1, they were told they would repeat one of the trials at the end of the study. Because our participants in this study may have had concerns about their cognitive abilities (they are participants in studies on AD which frequently presents with memory impairment), everyone was offered the opportunity to complete the 2-back a final time for a \$2 dollar bonus at the end of the study. This bonus was in addition to a flat completion fee of \$15. The ICC for this version of COG-ED was estimated as 0.54.

Additional Measures

We also administered the NASA Task Load Index after each level of the N -back task during the familiarization phase. In the NASA Task Load Index, participants rate their perceived mental workload on each level of the N -back on six domains (Mental Demand, Physical Demand, Temporal Demand, Effort, Performance, and Frustration). The scales were scored from *low* (1) to *very high* (21) and thus higher scores are indicative of greater effort. We used the Effort rating scores from the NASA for the 2-, 3-, and 4-back task as a measure of subjective effort (the 1-back was ignored because it serves as the baseline for the COG-ED task). We also administered the Need for Cognition Scale, as described in Experiment 1.

Statistical Analyses

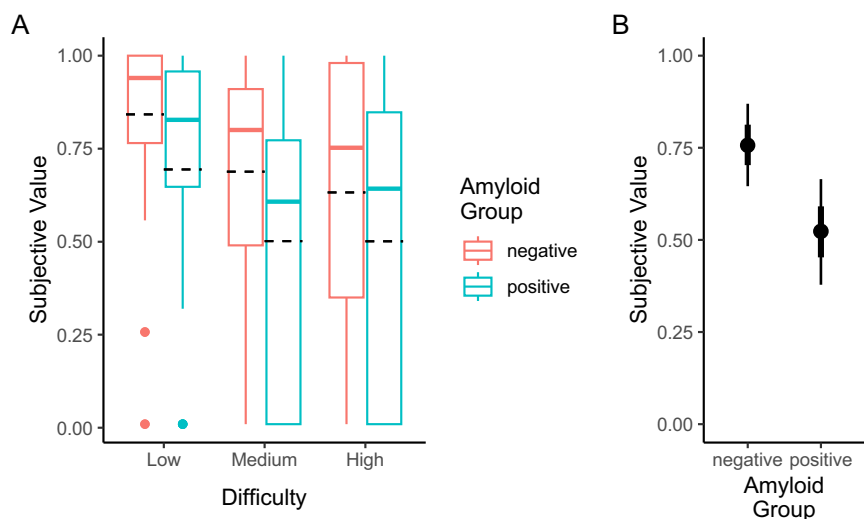
SVs were analyzed using a Bayesian mixed-effects model with fixed effects of “difficulty” (2-back, 3-back, or 4-back) and group (amyloid positive vs. amyloid negative) and the difficulty by group interaction. We also included the effects of age and APOE status as covariates. The effect of difficulty was modeled as a linear trend and other factors as dummy codes (reference group = amyloid negative, APOE group = no E4 allele). SVs were modeled with a student's t distribution to allow for heavy tails and prior distributions were designed to be relatively wide. More information on model fitting and convergence criteria are reported in the [Supplemental Materials](#). Results are reported as the mean estimate of the posterior with a 95% CI. An effect with an associated CI that excludes zero can be considered statistically significant.

Results

Mean SVs for each difficulty condition and amyloid group are plotted in Panel A of [Figure 5](#). Neither the effect of age ($\beta = 0.01$, CI [$-0.01, 0.02$]) nor of APOE status ($\beta = 0.09$, CI [$-0.10, 0.28$]) were significant. However, results revealed a significant effect of amyloid group on SV ($\beta = -0.24$, CI [$-0.42, -0.06$]), indicating that cognitive effort cost was higher for amyloid positive participants relative to the amyloid negative individuals (Panel B in [Figure 5](#)). The main effect of difficulty condition was also significant ($\beta = -0.07$, CI [$-0.12, -0.03$]), indicating that cognitive costs increased as task load increased. The group by difficulty interaction was not significant ($\beta = 0.02$, CI [$-0.05, 0.08$]). Posterior parameter distributions are plotted in the [Supplemental Materials](#). Importantly, the amyloid group difference persisted even after controlling for N -back performance in the familiarization task ($\beta = -0.19$, CI [$-0.38, -0.01$]).

Results from the Effort subscale of the NASA Task Load Index revealed a significant main effect of condition ($\beta = 1.62$,

Figure 5
Performance on the COG-ED Task in Experiment 2

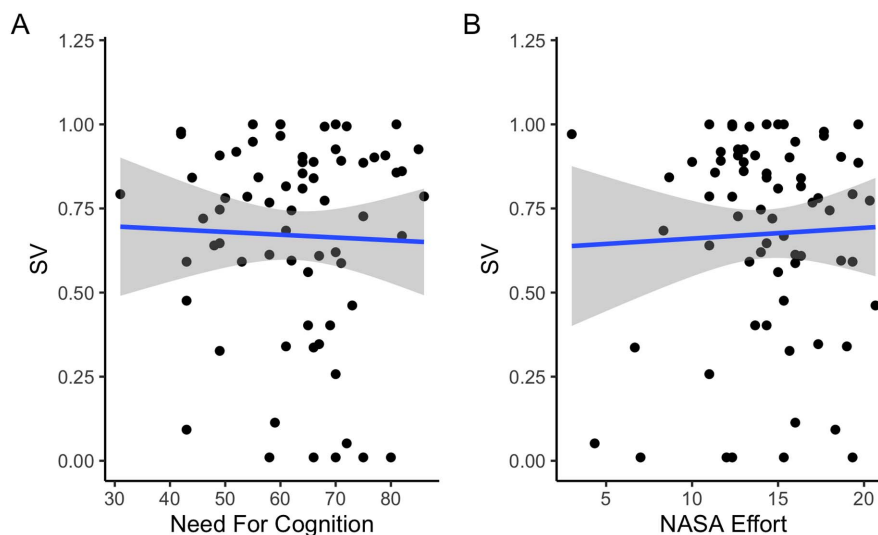


Note. Panel A: Boxplots of average SVs for each level of difficulty in Experiment 2. Solid lines represent the median value and the dashed lines represent the means. Panel B: Main effect of amyloid group (collapsed across difficulty). SV = subjective value; COG-ED = cognitive effort discounting. See the online article for the color version of this figure.

CI [1.16, 2.12]), indicating that effort ratings increased across *N*-back conditions as expected. However, in contrast to COG-ED, the effect of amyloid group was not significant ($\beta = -0.47$, CI [-2.6, 1.6]), and there was no interaction between condition and amyloid group ($\beta = -0.35$, CI [-1.19, 0.46]). In addition, the effect of amyloid group was not significant in the Need for Cognition Scale ($\beta = -2.17$,

CI [-9.4, 5.0]), indicating the two groups did not differ on either of these self-reported metrics. Moreover, neither the Need for Cognition Scale ($r = -0.03$, CI [-0.27, 0.19], Figure 6A) nor the average effort rating from the NASA ($r = 0.04$, CI [-0.19, 0.25], Figure 6B) was correlated with average SVs from the COG-ED.

Figure 6
Bivariate Relationships Between Need for Cognition and COG-ED SV (Panel A) and NASA Effort Subscale (Averages Across Conditions) and COG-ED SV Averaged Across Conditions (Panel B)



Note. COG-ED = cognitive effort discounting; SV = subjective value. See the online article for the color version of this figure.

Discussion

The goal of Experiment 2 was to test the hypothesis that individuals with elevated amyloid burden would experience greater cognitive effort costs than individuals with normal amyloid levels. This hypothesis was clearly supported. Participants who were considered amyloid positive based on well-established pathology cutoffs, experienced greater cognitive effort costs, as indexed by the COG-ED relative to those who did not meet the amyloid positivity threshold. In contrast, self-report measures of cognitive effort cost (i.e., the NASA and Need for Cognition Scale) did not show the same group difference. These contrasting patterns support the contention that performance-based measures of cognitive effort cost are a more sensitive marker of AD risk than self-report questionnaires.

General Discussion

There is a large heterogeneity in the rates of cognitive change associated with healthy aging and AD. One identified factor that may moderate rates of cognitive decline is engagement with cognitively effortful activities. Motivational selectivity accounts (Hess, 2014; Swirsky & Spaniol, 2019) suggest that older adults are less likely to engage in intellectually stimulating activities due to increased cognitive effort costs combined with a desire to preserve limited cognitive resources or to pursue goals that are the most personally meaningful. The overarching aim of this project was to test three critical hypotheses regarding age-related differences in cognitive effort costs. Specifically, we examined whether effort costs (a) are stable and domain-general across tasks, (b) are due to age-related differences in WM capacity, or (c) are due to accumulation of amyloid, which is a neurobiological hallmark of AD.

Our analysis of Experiment 1 supported our first hypothesis. We utilized online versions of the COG-ED to extend prior work (McLaughlin et al., 2021; Westbrook et al., 2013), by acquiring larger sample sizes, and implementing a within-subjects design, that enabled estimation and comparison of age-related differences in effort costs across two separate cognitive domains (WM and speech comprehension in noise). When compared to a similar cohort of younger adults, a clear age effect was found, such that the older adults experienced greater cognitive effort costs than younger adults, and this was true in both cognitive domains. These findings provide an important replication of prior work conducted in laboratory settings and point to the robustness of this phenomenon. Moreover, we demonstrated that effort costs were highly correlated across the two tasks in older adults, implying a stable, underlying construct that is being measured by the COG-ED paradigm. Indeed, the correlation was significantly larger in older adults as compared to a younger adult sample collected by Crawford et al. (2022).

The finding of increased COG-ED correlations among older adults might be expected based on the principle of dedifferentiation (Baltes et al., 1980). Briefly, the observation that cognitive abilities become more tightly correlated in older age may suggest the presence of a common mechanism, such as processing speed (Salthouse, 1996) or cognitive control/WM (Braver & Barch, 2002) or sensory changes (Baltes & Lindenberger, 1997), that underlies the majority of cognitive decline in older adults. Thus, to the extent that two different tasks increasingly rely on the same

underlying mechanism in older adults, estimates of costs across those tasks should also be more tightly correlated.

Surprisingly, Experiment 1 did not support our second hypothesis. In particular, cognitive effort costs were not correlated with WM capacity even in the WM version of COG-ED, despite robust age differences in capacity between our younger and older participants (Supplemental Figure S3). We had expected that individuals with overall lower cognitive ability (i.e., lower capacity) would have fewer cognitive resources to apply to any given task load and thus find it more effortful, as compared to individuals with relatively higher capacity. Alternatively, it is possible that individuals who have lower SVs simply exert less effort when performing the WM assessments, thus confounding our measurement of capacity. Regardless, no significant relationship between COG-ED outcomes and WM was found in the present study. Nevertheless, it should also be noted that this lack of correlation with WM capacity fails to replicate our own prior findings, in which we observed a correlation in older adults, between cognitive effort costs and in a speech comprehension task and WM capacity (McLaughlin et al., 2021). Conversely, the absence of the correlation with WM capacity was also observed by Crawford et al. (2022) in a younger adult sample. Thus, it seems reasonable to conclude that WM capacity is minimally related (if at all) to age effects in perceived cognitive costs in the COG-ED paradigm. Nevertheless, one possibility that should be further investigated is that the relationship between WM and COG-ED performance might be impacted by test administration format, as our results and those of Crawford et al. (2022) were obtained with online samples, whereas the significant correlations found in McLaughlin et al. (2021) were present during an in-person laboratory-based study. In addition to presentation format per se, online testing also removes the ability to test participants' hearing ability. Because hearing loss can increase cognitive demands during listening (Koeritzer et al., 2018; McCoy et al., 2005; McLaughlin et al., 2021), individual differences in hearing sensitivity may play a role in cognitive effort costs present on the speech comprehension COG-ED.

We did find clear support for our third hypothesis, in which we tested a candidate neurobiological explanation for *why* cognitive effort costs may increase in older adults was supported. Specifically, it is known that preclinical levels of AD pathology (specifically amyloid) are present in nearly half of the "healthy" older adult population (Jack et al., 2017). Amyloid accumulates in the healthy adult brains due in part to a reduced ability to "clear" amyloid. The "waste management" account of cognitive effort costs (Holroyd, 2016) suggests that release of amyloid is the marker of effort, and when levels of amyloid reach a critical level, effortful engagement is curtailed. Therefore, our straightforward hypothesis was that individuals who have an impaired ability to clear amyloid, and hence significant amyloid accumulation, would experience greater cognitive effort costs. In our data, individuals who were positive for amyloid based on either the CSF A β 42/A β 40 ratio or PET imaging markers expressed lower SVs on COG-ED (indicating increased cognitive effort costs) relative to amyloid negative controls. This finding provides strong support for the role of amyloid in producing disproportional changes in cognitive effort costs among older adults. Further, the results might suggest that the age-related differences in cognitive cost between younger adults and "healthy" older adults may be attributable at least in part to undetected amyloid in a portion of the older adult sample.

An additional aim of this project was to test the hypothesis that our behavioral measures from the COG-ED task would be more sensitive to amyloid pathology than questionnaire-based metrics of effort. This hypothesis was also supported. Specifically, there were no group differences on either the Effort subscale of the NASA Task Load Index or the Need for Cognition Scale in our sample. Thus, it was *only* the COG-ED task that showed an effect of amyloid burden, highlighting the importance of this marker in preclinical AD and the need for continued study of cognitive effort. The current findings replicate prior work (Westbrook et al., 2013) in showing the COG-ED task can better account for age differences than the NASA Task Load Index, pointing to the importance of using behavioral measures of cognitive effort. Additionally, in a study of younger adults, the COG-ED was the only predictor of effortful activities in daily life, when using experience sampling methods (Culbreth et al., 2020), and similar results have recently been observed in older adults (Crawford et al., 2023). Thus, it would be highly significant to determine if the additional predictive power of the COG-ED in naturalistic study settings might be mediated by differences in amyloid burden.

As the COG-ED task was developed based on principles from economic decision-making literature, it is useful to consider how discounting behavior is correlated in other domains and whether such correlations are influenced by age. For example, in Seaman et al. (2018), a life span sample of adults completed a physical effort discounting task (e.g., smaller rewarding for fewer presses of a button or a larger reward for more presses) and classic versions of probability (smaller reward with a higher probability vs. a larger reward with a smaller probability) and temporal discounting (a smaller reward now vs. a larger reward after a variable delay). Interestingly, there was no evidence for a relationship between age and effort or probability discounting and limited evidence of a small relationship between age and temporal discounting. Moreover, discounting rates across the three tasks were not correlated with each other, although a previous study did reveal a small relationship between temporal and effort discounting (Seaman et al., 2016). In contrast, Westbrook et al. (2013) showed that cognitive effort discounting (reflected by the COG-ED) was modestly correlated with a standard delay-discounting task ($R^2 = 0.14$), suggesting that there may be something unique about age, cognitive effort, and the ability to predict discounting of other cost variables, such as delay or risk. Thus, future work would benefit from examining domain-general discounting behavior (e.g., COG-ED) and their neurobiological correlates.

There were many strengths to this study including replication of age effects in cognitive effort costs even when increasing the sample size of the older adults relative to prior studies, and in sampling two different cognitive domains. The sample from Experiment 2 was carefully clinically phenotyped by trained clinicians to ensure no presence of dementia symptoms and thus differences in cognitive effort costs could more readily be attributed to pathology. However, some limitations should be noted. Experiment 1 was conducted in a convenience sample of older adults who participate in research studies online for monetary compensation. Thus, their motivations for completing the task (i.e., receiving more money) may have differed from a sample of volunteers who would choose to participate in a laboratory setting. This concern is mitigated to a large extent by the similarity in age effects across our online studies and those conducted in the lab (McLaughlin et al., 2021; Westbrook et al., 2013). Nevertheless, as mentioned above, this may have contributed to the failure to replicate WM capacity effects in the COG-ED. Moreover, the older adults in

our Experiment 1 were administered an identical protocol as the younger adults; however, the two data sets were not acquired contemporaneously and thus temporal or cohort differences must be considered. Finally, though we aimed to identify a domain-general cognitive effort cost mechanism, it should be noted that we tested only two cognitive domains and as such our findings may not generalize to other cognitive domains such as episodic memory or lexical processing. Moreover, although SV estimates were significantly correlated across the domains, the shared variance was fairly small, suggesting a large amount of task-specific influences. The sample in Experiment 2 comes from a highly educated, mostly White cohort which may not be representative of the general population. Moreover, as this study was conducted during COVID-19 closures, biomarker assessments at the Knight ADRC were halted and hence we were required to allow a relatively long interval (i.e., 5 years) between the nearest biomarker measurement and the COG-ED task.

The studies presented here are just one step in a larger research program investigating age differences in cognitive effort costs. An important next step will be to determine how increased amyloid burden fits into the biological pathways that have already been implicated in moderating cognitive effort costs (e.g., Westbrook et al., 2019, 2020). For example, is it the case that amyloid burden effects on cognitive effort costs are mediated by changes in dopamine receptors in ventral striatum or alternatively by norepinephrine tone within the dorsal anterior cingulate? Additionally, it is important to more systematically test whether biological markers, such as amyloid burden, and laboratory tasks, such as the COG-ED, predict individual variation in effortful task engagement under naturalistic conditions possibly using ecological momentary assessment methodologies as mentioned (Crawford et al., 2022; Culbreth et al., 2020). Moreover, additional control variables that may explain additional age-related variance in cognitive effort costs should be explored. Finally, we used monetary incentives that were largely hypothetical to produce estimates of cognitive effort costs. It will be important to replicate these findings using rewards that may be more meaningful to older adults based on the SOC framework (e.g., social or health rewards; Lockwood et al., 2021; Seaman et al., 2016). Nevertheless, our results point strongly to the presence of a stable, domain-general "trait" indexed by cognitive effort costs and point to amyloid as a key factor producing such costs. In fact, it was *only* the COG-ED that showed a difference due to amyloid (not self-reported scales), highlighting the importance of this marker in preclinical AD and the need for continued study of cognitive effort in healthy aging.

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Received March 29, 2022

Revision received February 16, 2023

Accepted February 23, 2023 ■