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Preliminary Acceptability and Efficacy of an Expected Value Decision-Making Training Intervention among Older and Younger Adults: A Pilot Study

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Abstract

Effective decision-making is critical to successful aging as many high-stakes medical and financial decisions must be made as one ages, yet decision-making quality often declines with age. This pilot study evaluated the feasibility, acceptability, and preliminary efficacy of an Expected Value (EV) maximization training designed to optimize risky decision-making performance in older adults. A two-week longitudinal pilot study was conducted with healthy older (n=30) and younger (n=35) adults. Participants completed a risky choice task at baseline, immediate follow-up, and two-week follow-up. EV maximization training entailed a didactic video plus a hands-on repeated choice training task with feedback. Feasibility was supported among older adults (0% attrition) but limited in younger adults (39% attrition). Acceptability ratings exceeded expectations (≥75% positive) and were significantly higher in older than younger adults. Older adults' performance improved from 45% accuracy at baseline to 84% at immediate posttest and 75% at two-week follow-up, whereas younger adults showed no benefit. EV maximization training was feasible, well-accepted, and showed evidence of preliminary efficacy in older adults.

Introduction

Effective decision-making is critical for successful aging. For example, high-stakes medical and financial choices can have lasting consequences (Stern al., 2000). Nevertheless, people consistently engage in suboptimal risk-reward trade-offs (Kahneman & Tversky, 1979) that are magnified with age (Tymula et al., 2013). Thus, there is a strong need to develop interventions that optimize decision performance in older adults.

Decisions under risk characterize choices in which the probabilities of possible options are known (Johnson & Busemeyer, 2010). One of the most well-established theories to explain how people make decisions under risk include Expected Utility Theory (EUT; Edwards, 1954). EUT builds upon the expected value (EV) principle that assumes rationality: individuals weight outcomes by their likelihood and choose the option with the highest mathematical value (Edwards, 1954). EUT proposes that instead of the objective value of an outcome, individuals assign a utility, or a subjective desirability or value, to each outcome. EV-based decisions involve a simple decision rule that can promote objective weighting of probabilities and outcomes.

Whereas EUT highlights the normative benchmark of maximizing EV, research consistently shows that older adults deviate more strongly from this benchmark than younger adults. Studies have consistently observed that older adults are less likely to choose high-EV options than younger adults and thus exhibit suboptimal performance in decisions under risk (Bolenz & Pachur, 2024; Pachur et al., 2017; Tymula et al., 2013). While younger adults tend to integrate both outcome and probability information, older adults rely more heavily on either outcome magnitudes (Bolenz & Pachur, 2024; Johnson & Busemeyer, 2010), or probabilities (Best & Freund, 2018; O'Brien & Hess, 2020). Specifically, in gain-framed decision

contexts that present a tradeoff in a sure versus a risky option, older adults appear to weigh probabilities more heavily than expected values (Best & Freund, 2018; O'Brien & Hess, 2020).

These findings are consistent with work showing that older adults tend to rely on simpler, less cognitively demanding decision-making strategies, which reflects an adaptive, compensatory response to age-related cognitive decline (Mata et al., 2007; Worthy & Maddox 2012; Worthy et al., 2014; Worthy et al., 2016). Rather than pursuing computationally intensive strategies that optimize decision quality, older adults often adopt information-frugal heuristics that prioritize satisficing decisions in lieu of exerting greater cognitive effort (Mata et al., 2007). Such heuristics involve considering fewer pieces of information but allocating more time evaluating each one when making decisions (Peters et al., 2007). This compensatory process reduces cognitive load and aligns with the resource-rational strategy selection model in which older adults conserve cognitive resources by choosing strategies that balance expected outcomes with the effort required to execute a decision (Bolenz & Pachur, 2024).

Despite consistent evidence that older adults make suboptimal decisions under risk, relatively few efforts have been made to translate this knowledge into interventions to improve such decisions. The present study seeks to address this gap. Because older adults are less likely to integrate EV information compared to younger adults, (Bolenz & Pachur, 2024; Pachur et al., 2017; Tymula et al., 2013), EV maximization training may may offer a promising approach to enhance decision performance. EV maximization offers a straightforward, prescriptive strategy: multiply each outcome by its probability and choose the high-EV option. Indeed, prior work shows that providing explicit EV information as a decision aid enhances financial risk-taking and rational choice behavior in older adults (Samanez-Larkin, Wagner, & Knutson, 2011). Building on this work, EV maximization training may reduce reliance on suboptimal heuristics by clarifying which information to attend to and how to integrate it.

This pilot study sought to design, implement, and evaluate the acceptability and preliminary efficacy of a structured decision-making intervention tailored for older adults. Specifically, we developed an intervention that teaches the simple yet effective strategy of maximizing expected values. The intervention sought to help older adults reallocate cognitive resources by clarifying which information to consider and how to use it. We expected high intervention acceptability (>75% positive ratings) and improved decision performance (≥10% change from baseline). In addition, we collected qualitative feedback to identify strengths of the intervention and areas for improvement to inform future intervention development.

Method

Participants

The pilot study was approved by the university Institutional Review Board (IRB2023-0511) before procedures were implemented. Younger adults were college students who were recruited from the online research participant pool through the university. Older adults were recruited through fliers, newsletters,

and email at local community centers, educational centers (e.g., Osher Lifelong Learning Institute, Institute for Engaged Aging), gyms (e.g., YMCAs), and libraries. For the in-person baseline assessment, older adult participants received $30 cash, and younger adults received partial course credit or extra credit. All participants were compensated with a $20 Amazon eGift for completing the remote two-week follow-up assessment. Participants met inclusion criteria if they were fluent in English and within the age range of 18–30 years for younger adults or 60–85 years for older adults. All older adults who completed the study passed a cognitive pre-screening virtual assessment with a Montreal Cognitive Assessment (MoCA) score of 24 or higher and had no prior diagnosis of neurological illnesses, including Alzheimer's disease, brain aneurysm, brain injury, brain tumor, dementia, epilepsy, multiple sclerosis, muscular dystrophy, neuropathy, Parkinson's disease, spinal cord injury, or stroke.

An a priori power analysis in G*Power 3.1.9.7 using a two-tailed paired t-test with α = 0.05 and 80% power indicated that 30 participants per age group would be needed to detect a medium effect size (Cohen's d = 0.50) in pre–post changes from baseline to follow-up. The recruitment goal was to have at least 30 older adults and 30 younger adults complete both the baseline and two-week follow-up assessment. Thirty older adults and 57 younger adults completed the baseline session. All of the older adults completed both assessments, and 61% (n = 35) younger adults who participated in the baseline assessment also completed the two-week follow-up.

Design

The pilot study entailed a two-group quasi-experimental longitudinal study with age group (older vs. younger adult) as the between-subjects factor and time (baseline vs. two-week follow-up) as the within-subjects factor. The baseline assessment and immediate follow-up task were conducted in-person, and the two-week follow-up was conducted remotely.

Measures

Behavioral Decision-Making Assessments. Decision-making performance was assessed at baseline, immediate follow-up, and two-week follow-up using a binary risky choice task. On each trial, participants chose between two doors representing a trade-off between outcome probability and reward magnitude (±$0–$25). Trials included both gains and losses (≈ 50% each), and 10% of all trials entailed a tradeoff between a sure (100% or 0%) and risky outcome; all other trials entailed risky-risky outcome tradeoffs. Probabilities ranged from 0% – 100% and were presented in increments of 5 (i.e., 0, 5, 10, 15, etc). All options included in statistical analyses included one high-EV option and one low EV option. The underlying payoff structure in terms of the distribution of reward magnitudes, probabilities, and expected values was held constant across assessments to maintain comparable task difficulty, but specific probability–reward pairings were re-randomized so that no decision was repeated.

Each assessment included two manipulation check trials that offered a guaranteed large-magnitude reward (e.g., 100% chance of $20) versus a risky low-magnitude reward (e.g., 10% chance of $3). Participants completed 40 trials at baseline and immediate follow-up, and 50 trials at two-week follow-

up. Consistent with past research (Bolenz & Pachur, 2024), the correct choice was defined as the option with the higher expected value, and performance (e.g., decision accuracy) was operationalized as the proportion of correct choices. No feedback was provided, and participants had unlimited time to respond. Task instructions are in Appendix 1 of the Supplementary Materials.

Decision-Making Training Intervention. In line with past work with decision aids (Samanez-Larkin et al., 2011), the intervention was grounded in the EV principle, which specifies the optimal choice among risky alternatives as the one with the greatest expected value: the sum of all possible outcomes weighted by their probabilities (Edwards, 1954). In risky decision contexts, EV provides a benchmark for objectively maximizing gains by balancing reward magnitude against probability (Edwards, 1954; Kahneman & Tversky, 1979). This strategy can mitigate biases, such as probability weighting and loss aversion, which may be exacerbated in older adulthood (Henninger et al., 2010; Peters et al., 2007).

The intervention was designed to improve higher-EV choice selection. It consisted of two components: an instructional video explaining EV principles with examples (Appendix 2) a 200-trial hands-on training task (100 gain-framed and 100 loss-framed) with binary risky choices. The task was the same as the behavioral decision-making task, except that feedback was provided on each trial. The task matched the main decision-making paradigm but provided trial-by-trial feedback: “Correct” for optimal choices, or the correct option with a brief explanation for errors (Fig. 1). Participants received 30-second breaks every 50 trials and could earn up to $10 based on performance.

Training Acceptability. Quantitative acceptability questions measured satisfaction, interest, and perceived usefulness, of the training with responses on a five-point Likert scale raining from 1 (*Strongly Disagree)* to 5 (*Strongly Agree*).

Open-Ended Participant Feedback. Participants responded to two open-ended questions designed to capture their subjective evaluation of the training. Specifically, they were asked to describe what they liked most about the training and to provide suggestions for how the training could be improved.

Procedure

Supplementary Table 1 outlines the baseline assessment activities. All baseline activities were administered in the laboratory on an iPad using *Decision Coach*, an application developed by our team for this study. At baseline, participants provided written informed consent, demographics information (age, gender, and level of education), reviewed task instructions, completed two practice trials, and performed 40 baseline decision-making trials. They then watched the training video, reviewed training instructions, completed 200 training trials, and performed 40 immediate follow-up trials, followed by quantitative and open-ended acceptability feedback. The baseline session lasted ~ 90 minutes.

Twelve days after the baseline assessment, participants were emailed a Qualtrics link to complete the 50-trial two-week follow-up decision-making task, which was due within 21 days of baseline. The follow-

up took ~ 15 minutes. Upon completion, participants received a code for a $20 Amazon eGift card. Data analysis details are provided in the Supplementary Materials.

Data Analysis

To examine the effect of the intervention on decision-making performance, a generalized linear mixed-effects regression (*glme*) was conducted. The dependent variable was participants' binary decision on each trial for door selection, coded as correct or incorrect, with the door offering the higher expected value defined as the correct option. The fixed effects (independent variables) in the model included age group (younger vs. older adults), time (baseline vs. immediate post-intervention, and two-week post-intervention), and trial type framing (gain vs. loss). Moreover, it is possible that the intervention may improve decision performance for a subcategory of decision scenarios, such as low-probability losses or high-probability gains. To address this possibility, separate exploratory analyses that included probability and reward magnitude as moderators were also performed. To account for individual differences, a random intercept for Participant ID was included. To further investigate this interaction, post-hoc analyses were conducted. The dataset was first split by age group. Then two separate *glmer* models were conducted for each age group to examine the two-way interaction between time and trial type framing on decision performance.

Though not the focus of the intervention, a generalized linear mixed-effects regression analysis with age group, time, and trial type framing as predictors was also performed to explore potential age differences on risky choice. Risky choice was defined as choosing the low-probability option during the task.

Each of the acceptability items was analyzed by calculating the frequency of participants who strongly or somewhat agreed with each statement. Two-sample z-tests for proportions were used to compare item response frequencies between older and younger adults. To explore whether greater intervention acceptability predicted greater training improvements benefits, bivariate correlations were also conducted between acceptability responses and decision performance.

Qualitative analysis followed the six-stage thematic analysis approach (Braun & Clark, 2006). Using an inductive approach, open coding was conducted on de-identified data with participants' age group removed to reduce potential bias. Axial coding was then applied to identify broader themes within these categories. Finally, themes were re-linked to the labeled dataset, and frequency analyses by age group were conducted.

Results

Sample Characteristics and Attrition

Thirty older adults aged 60–85 (60% female, M_{age}=68.80 years, SD_{age}=6.67 years, $M_{education}$=16.60 years, $SD_{education}$=1.59) and 35 younger adults aged 18–21 (89% female, M_{age}=18.43 years, SD_{age}= 0.82 years,

$M_{education}$= 12.26 years, $SD_{education}$=0.61 years) completed both baseline and follow-up assessments and were included in final analyses described below. No participants failed the manipulation checks trials. Despite the same financial incentive offered for two-week follow-up participation, attrition rates significantly differed between older (0%) and younger adults (39%), $Z = 3.940$, $p < 0.001$. The younger adults who did not complete the two-week follow-up did not differ in baseline decision performance ($p = 0.674$) or immediate post-test performance ($p = 0.784$) from those that completed the full study. Gender differences ($p = 0.275$) were also not observed; however, the younger adults that were lost to follow-up were approximately one-year older ($M = 19.08$, $SD = 1.38$) than those that completed the full study ($M = 18.42$, $SD = 0.806$).

Among participants that completed both the baseline and follow-up assessments, older adults' ($M = 0.451$, $SD = 0.115$) decision performance was significantly worse than younger adults' ($M = 0.650$, $SD = 0.078$) at baseline $t(63) = 8.262$, $p < 0.001$. However, no difference in baseline risk-taking behavior was observed between older ($M = 0.33$, $SD = 0.20$) and younger ($M = 0.37$, $SD = 0.18$) adults, $t(63) = -0.73$, $p = 0.47$.

Training Intervention Preliminary Efficacy

Overall, older adults' decision performance improved from 45% accuracy at baseline to 84% at immediate follow-up and 75% at two-week follow-up. In contrast, younger adults performed better than older adults at baseline (65% accuracy) but did not improve at immediate follow-up (68%) or two-week (54%) follow-up. Specifically, regression model results showed a significant three-way interaction between time, age group, and trial type framing ($\beta = 0.560$, $p = 0.022$, Fig. 2A, Supplementary Table 2). On gain-framed trials, older adults were more likely to choose the correct door immediately ($\beta = 0.917$, $p < 0.001$) and at two-week follow-up ($\beta = 0.645$, $p < 0.001$) compared to baseline (Supplementary Table 3). Performance did not significantly differ between immediate and two-week follow-up assessments (β=-0.272, $p < 0.217$). On loss-framed trials, performance improved immediately after the intervention ($\beta = 1.403$, $p < 0.001$). While performance declined at two-week post-intervention (β=−0.849, $p < 0.001$), it remained significantly above baseline ($\beta = 0.554$, $p < 0.001$).

For younger adults (Supplementary Table 4), performance in gain-framed trials remained unchanged immediately post-intervention but declined at two-week follow-up (βs = − 0.155−−0.658, $p < 0.001$). In loss-framed trials, performance improved immediately ($\beta = 0.479$, $p < 0.001$) but decreased at two-week follow-up (β=−0.670, $p < 0.001$); thus, performance benefits were not maintained.

Exploratory regression analyses that included the probability of reward (Supplementary Table 5) and the magnitude of the reward (±$0 - $25; Supplementary Table 6) as moderators did not reveal any significant interactions with age in predicting decision performance. Thus, the intervention did not differentially impact older adults' decision performance on a particular across decision scenarios varying in probability or magnitude.

Effects of the Training Intervention on Risky Choice

Participants, regardless of age, were more likely to select the risky option when trials were framed as losses compared to gains (β = 1.13, p < 0.001). In addition, individuals across both age groups demonstrated greater risk-taking immediately after training (β = 1.045, p < 0.001) and at the two-week follow-up (β = 0.949, p < 0.001) compared to the baseline phase.

Furthermore, there were two significant two-way interaction effects: time × trial type and age group × trial type, ps < 0.05. Simple effect analysis was conducted to further unpack these interactions. For gain trials, risk-taking significantly increased from the baseline to the immediate phase (β = 0.951, p < 0.001) and remained elevated at the two-week follow-up (β = 0.823, p < 0.001), with no difference between the immediate and two-week follow-up (β=-0.128, p = 0.256). In contrast, for loss trials, risk-taking significantly decreased from baseline to the immediate follow-up (β=-0.25, p = 0.010), did not differ between baseline and two-week follow-up (β = 0.14, p = 0.21), and increased again from the immediate to two-week follow-up (β = 0.40, p < 0.001).

In terms of the age group × trial type interaction, results showed that older adults were less likely to choose risky options than younger adults on gain trials (β = 0.223, p = 0.032), while there was no significant age difference observed among loss trials (β = 0.026, p = 0.800).

Decision Training Acceptability

Participants' mean ratings corresponded to 'Somewhat Agree' (4/5) for training satisfaction, interest, enjoyment, perceived challenge, usefulness, and perceived learning. Older adults reported significantly higher satisfaction, interest, enjoyment, and challenge than younger adults, with no age differences in usefulness, confusion, or learning (Supplementary Table 7).

Table 1
Proportion of Participants that Agree with Training Acceptability Items

Item (% Strongly or Somewhat Agree)	Overall Sample (N = 65)	Older Adults (n = 30)	Younger Adults (n = 35)	P-Value
I am satisfied with the decision training I completed as part of this study.	81.54%	93.33%	71.43%	0.024
The training was interesting.	86.15%	96.67%	77.14%	0.024
I enjoyed the training.	63.08%	86.67%	42.86%	< 0.001
The training was challenging.	76.92%	96.67%	60.00%	< 0.001
The training was useful.	76.92%	86.67%	68.57%	0.087
The training was confusing.	33.85%	30.00%	37.14%	0.547
I feel like I learned new information from this training.	83.08%	90.00%	77.14%	0.171

At least 75% of participants, regardless of age, strongly or somewhat agreed that the training was interesting, challenging, and useful. Notably, 82% of participants (93% older adults vs. 71% younger adults) were satisfied with the training, and 86% (97% older adults vs 77% younger adults) found the training interesting (Table 1). Greater training interest and enjoyment was associated with greater improvements in decision performance at immediate and two-week follow-up, regardless of age (Supplementary Table 8).

Qualitative Results

Thematic analysis revealed that participants valued the skill and knowledge acquisition

(n = 27), cognitive challenge (n = 26), training design and delivery (n = 19), and practical relevance (n = 7) of the training. More younger adults noted training design and delivery as a strength than older adults (40% vs. 17%, Z=-2.06, p=.04, Supplementary Table 9).

Suggested improvements included changes to the training length and/or structure (n = 22), greater engagement (n = 15), clearer explanations (n = 15), decision aids (n = 8), and user experience enhancements (n = 7). More younger adults noted the length (46% vs.20%, Z=-2.18, p=.01) and user experience (20% vs. 0%, Z=-2.59, p=.03) as suggested improvements than older adults (Table 2). Further details of the open coding analysis and category identification are shown in the Supplementary Material.

Table 2
Thematic Analysis for Most Valued Aspects of the Training

Theme	Description	Examples	Age Group Frequencies	P-Value
Skill Acquisition and Knowledge Gain (n = 27)	Learning new decision-making strategies, math skills, and concepts	"Learning more about the possible reasons that I make decisions"	OA: 13/30 YA: 14/35	0.79
		"I liked that it taught me how to figure out the better option based on the percentage"		
		"It was a different way of thinking about decision making"		
Cognitive Challenge (n = 26)	Mental effort required by the training	"It was challenging: requires focus, analytics and problem solving"	OA: 12/30 YA: 14/35	1.00
		"I liked being able to put numbers to decisions"		
		"It was a good opportunity to use my brain and math skills"		
Training Design and Delivery (n = 19)	Training's format, features, and presentation	"I liked the video"	OA: 5/30 YA: 14/35	0.04
		"Liked the coins that fell down when you were right"		
		"The instant feedback in some parts was good"		
Practical Relevance (n = 7)	Perceived real-life applicability of the training	"I can utilize [the training] in the future when making decisions regarding risk and reward."	OA: 2/30 YA: 5/35	0.32
		"I liked the usefulness of the material"		
		"It taught me good skills that I would apply in life"		

Discussion

This pilot study evaluated the feasibility, acceptability, and preliminary efficacy of a novel expected value maximization training designed to optimize risky decision-making performance in older adults. Feasibility of delivery using the *Decision Coach* app was clear among older adults, who showed no attrition, but limited in younger adults who showed 39% attrition. Training acceptability was supported by high ratings (≥ 75%) of satisfaction, interest, perceived learning, and usefulness when averaging across the full sample and was higher among older compared to younger adults.

Consistent with prior research (Bolenz & Pachur, 2024; Pachur et al., 2017; Tymula et al., 2013), older adults were less likely to choose high-EV options at baseline. Critically, training led to substantial (67%) and lasting improvements in older adults' decision performance with no benefit observed in younger adults. Among older adults, improvements were robust across gain and loss contexts, though loss-related gains diminished over time. Younger adults showed no measurable improvement in either decision framing context.

Consistent with the classic framing effect (Tversky & Kahneman, 1981), participants, regardless of age, were more likely to choose the risky option when outcomes were framed as losses rather than gains. Thus, participants in this study exhibited heightened risk aversion in gain contexts but increased risk-seeking in loss contexts. Additionally, the observed increase in risk-taking following the intervention suggests that participants became more willing to engage with risky options after learning how to evaluate them based on probabilistic and outcome information. The finding that older adults were less likely than younger adults to choose risky options on gain trials aligns with prior evidence that aging is associated with greater risk aversion in reward contexts (Best & Freund, 2018; Lauriola & Levin, 2001; Mather et al., 2012). The absence of age differences on loss trials is consistent with past work (Richtmann et al., 2025) and suggests that both groups exhibited similar aversion to potential losses, consistent with research indicating that loss sensitivity remains relatively stable across adulthood (Seaman et al., 2018).

Older adults also reported higher overall acceptability than younger adults. Insights from the qualitative feedback help to explain these differences. While both older and younger adults valued the content and cognitive challenge of the training, nearly half of the younger adults critiqued its length and structure, and 20% suggested user experience improvements. In contrast, older adults expressed little concern about delivery format and instead prioritized content and applicability. These findings align with work on digital training preferences showing that younger adults emphasize efficiency, interactivity, and design, whereas older adults prioritize clarity, accessibility, and relevance (Aly et al., 2024; Czaja et al., 2019; Liu et al., 2025).

Limitations and Future Directions

Several limitations should be acknowledged. As a pilot study, the small sample limits generalizability and findings require replication. Differences in recruitment procedures between age groups may have

influenced motivation, although both groups were paid for follow-up assessments. Individual differences in numeracy, working memory, digital literacy, or education were not assessed but may moderate training efficacy. Because the training task and outcome task shared the same structure, improvements may partially reflect task-specific learning and practice effects rather than transfer of a generalized decision-making strategy. Future work should incorporate independent outcome measures to evaluate transfer. Similarly, it remains unclear whether benefits transfer to other forms of decision-making, such as decisions from experience or applied domains like financial, medical, health, or digital privacy contexts.

In line with the Selection, Optimization, and Compensation model (Baltes & Baltes, 1990), older adults are highly selective in how they allocate resources and more motivated when decisions are meaningful (Peters et al., 2007). One way to increase impact may be to incorporate real-world examples directly into the hands-on training phase rather than the didactic video alone. Additionally, the finding that greater training interest and enjoyment predicted stronger follow-up improvements regardless of age suggests that strategies to enhance engagement could amplify training efficacy.

Conclusion

To our knowledge, this pilot study is the first to demonstrate that expected value maximization training that combines a didactic video with hands-on practice and feedback can improve risky decision-making performance in older adults. These findings highlight the age-specific preliminary efficacy of the intervention and suggest that older adults, in particular, can adopt strategies that support more adaptive decision-making.

Statements and Declarations

Competing Interests: The authors declare no competing financial or non-financial interests.

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Figures

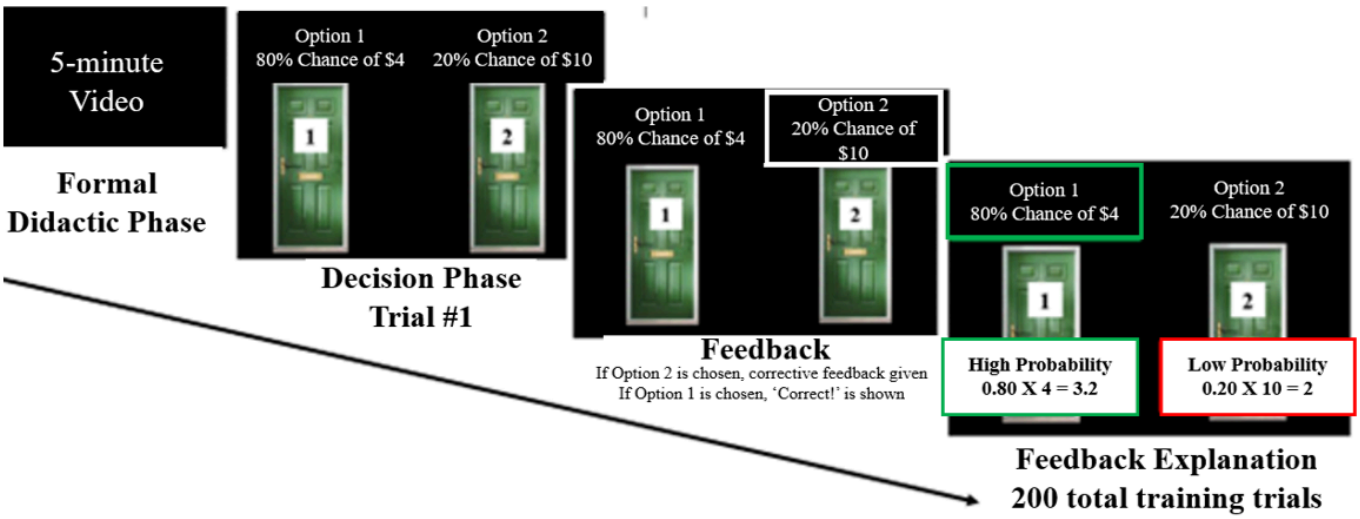


Figure 1

Sample training trial following the initial training video.

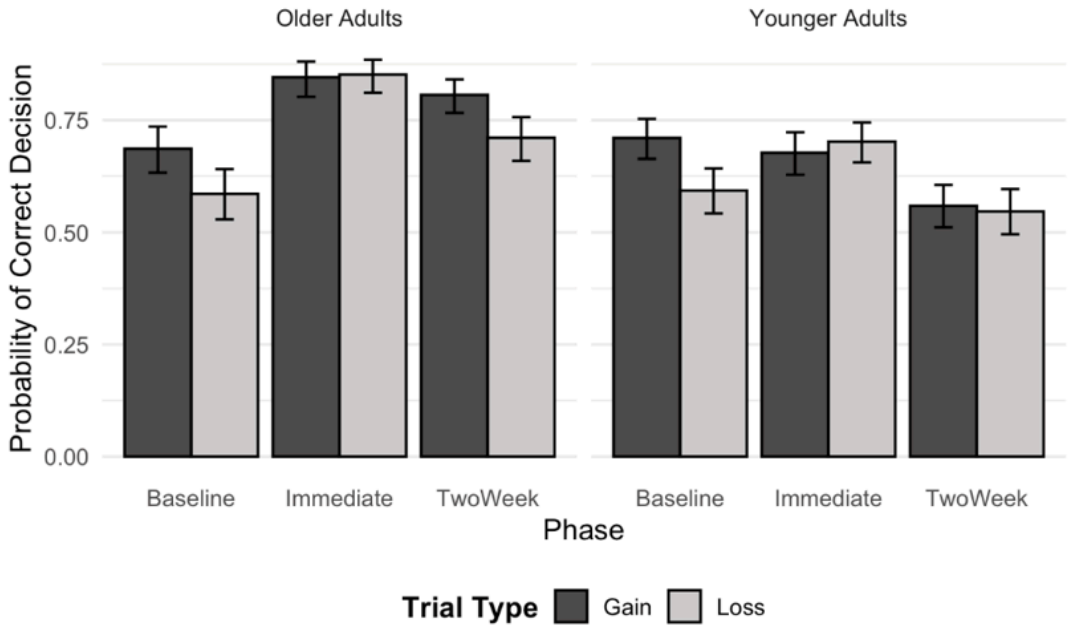


Figure 2

Probability of choosing the high EV option during the baseline, immediate follow-up and two-week follow-up behavioral assessments by age group and trial type (gains vs. losses). (Error bars represent standard error of the mean.

Supplementary Files

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- SupplementaryMaterials.docx