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Journal of Behavioral Decision Making

Provided in Cooperation with:
John Wiley & Sons

Suggested Citation: Zilker, Veronika; Pachur, Thorsten (2021) : Does option complexity contribute to the framing effect, loss aversion, and delay discounting in younger and older adults?, Journal of Behavioral Decision Making, ISSN 1099-0771, Wiley, Hoboken, NJ, Vol. 34, Iss. 4, pp. 488-503, https://doi.org/10.1002/bdm.2224

Received: 7 August 2020 | Revised: 20 September 2020 | Accepted: 30 November 2020

DOI: 10.1002/bdm.2224

RESEARCH ARTICLE

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Does option complexity contribute to the framing effect, loss aversion, and delay discounting in younger and older adults?

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Abstract

Recent findings suggest that the commonly observed preference for a safe over a risky option, which is more pronounced in older than in younger adults, is largely driven by differences in the complexity of those options. Here we examine whether option complexity also contributes to the emergence of the framing effect and loss aversion in risky choice as well as to delay discounting in intertemporal choice. All of these phenomena tend to be measured with choice problems that involve options differing in complexity. We also examine whether option complexity contributes to potential age differences in these phenomena. In each paradigm, we experimentally increased the complexity of the simpler option, thus reducing differences in the complexity of the options. We found no evidence for an effect of this manipulation on the framing effect nor on participants' preferences in the loss aversion task. On average, participants did not show loss aversion. Increasing the complexity of the option with an immediate reward in the intertemporal choice task made younger, but unexpectedly not older, adults less likely to choose this option. Our results thus indicate that preferences in tasks typically used to measure the framing effect, loss aversion, and delay discounting are only little affected by differences in option complexity.

KEYWORDS
aging, delay discounting, framing effect, loss aversion, option complexity, risky choice

1 | INTRODUCTION

Behavior in preferential choice tasks is often thought to reflect preferences for particular attributes of options, such as the risk or delay of their consequences. For instance, when asked to choose between a safe option and a risky option with different chances of winning or losing one of several rewards, people often prefer the safe option in the domain of gains and the risky option in the domain of losses (e.g., Kahneman & Tversky, 1979). This pattern is commonly thought to indicate risk aversion for gains and risk seeking for losses, and it is even more pronounced in older than in younger adults (e.g., Mather et al., 2012; Rutledge et al., 2016).

As Zilker, Hertwig, and Pachur (2020) have shown, however, safe and risky options differ not only in their risk but also in the amount of information to be processed. Safe options can be fully described by a single outcome and its probability (e.g., "100% chance to win 66"),

Data and code to implement all analyses are publicly available on the OSF: http://doi.org/10.17605/OSF.IO/BJ2TV. An earlier version of this manuscript, preceding peer review, was part of Veronika Zilker's PhD dissertation (Zilker, 2020).

whereas risky options consist of multiple outcomes and probabilities (e.g., "60% chance to win 90; 40% chance to win 30"). Therefore, in choices between safe and risky options, the options differ in complexity. These differences in option complexity can be a key driver of age differences in apparent risk aversion in choices between a safe and a risky option: Zilker et al. (2020) compared younger and older adults' behavior in choices between a simple safe and a risky option that differed in complexity to choices between similarly complex safe and risky options. To render safe options similarly complex to risky ones, the safe outcome was expressed as a mathematical term consisting of several pieces of numerical information (e.g., "100% chance to win (0.6 × 90) + (0.4 × 30)") rather than a single number (e.g., "100% chance to win 66"). Reducing the differences in complexity led to a decrease in the tendency to choose a safe gain over a risky gain in both age groups, and this effect was more pronounced in older than in younger adults. In fact, age differences in the tendency to prefer a safe gain over a risky gain disappeared when the differences in option complexity were attenuated. Option complexity also affected choice behavior and age differences therein in the domain of losses, but the effects were less pronounced overall than in the domain of gains.

These findings suggest that behavior in the common choice task pitting a simple safe against a more complex risky option, and age differences therein, may reflect a response to differences in option complexity rather than risk preference. Notably, also other prominent choice phenomena are often studied with tasks involving a choice between a simpler option and a more complex option—for instance, the paradigms used to measure the framing effect and loss aversion in risky choice and delay discounting in intertemporal choice. Does option complexity also contribute to choice behavior in these paradigms? Moreover, to the extent that there are differences between younger and older adults in these phenomena, do they reflect age differences in the response to option complexity?

This article investigates these questions by comparing behavior in standard choices between a simpler and a more complex option with behavior in choices where these differences in option complexity are attenuated. We also compare the behavior of younger and older adults in these task variants. Older adults are known to suffer from losses in fluid cognitive skills (Craik & Bialystok, 2006; Horn & Cattell, 1967; Zaval, Li, Johnson, & Weber, 2015). Moreover, differences between younger and older adults are often observed especially in cognitively demanding tasks (e.g., Frey, Mata, & Hertwig, 2015), and it has been proposed that older adults are more selective than younger adults in their engagement of cognitive resources in such tasks (Hess, 2014). It is therefore plausible that differences in option complexity have a particularly strong effect in older adults (a similar possibility was also explored by Mather et al., 2012). In the following, we first describe in more detail the three choice phenomena investigated, the tasks typically used to demonstrate them, and findings on age differences. We lay out how differences in option complexity may contribute to each phenomenon and age differences therein. We then report the findings of an experiment conducted to test whether the framing effect, loss aversion, and delay discounting, as well as age differences therein, are affected when complexity differences between the options are reduced.

1.1 | The Framing Effect

The tendency to choose a safe or a risky option depends critically on whether the possible outcomes are described as gains or as losses. The classic demonstration of this *framing effect* (Tversky & Kahneman, 1981) involved choices in a fictitious scenario in which a disease threatens to kill 600 people. In the positively framed condition, the options were described as follows: "If program A is adopted, 200 people will be saved. If program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved." In the negatively framed condition, the options were described as follows: "If program C is adopted, 400 people will die. If program D is adopted, there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die." Although A is equivalent to C and B is equivalent to D, most participants prefer the safe option (A) in the positive frame but the risky option (D) in the negative frame.

Framing problems typically involve a safe and a risky option. The safe option is simple to evaluate because it consists of only one outcome. The risky option is more complex, consisting of two possible outcomes and the associated probabilities. Given the findings of Zilker et al. (2020), it seems possible that these differences in option complexity may contribute to apparent risk aversion in choices about positively framed options and apparent risk seeking in choices about negatively framed options. Consistent with this possibility, a meta-analysis by Kühberger (1998) concluded that framing effects are more pronounced in choices between a risky and a safe option (which differ in complexity) than in choices between two risky options (which are more similar in complexity).

Evidence for age differences in the framing effect is mixed. Whereas some studies have found a stronger framing effect in older adults than in younger adults (Bruine de Bruin, Parker, & Fischhoff, 2007; Kim, Goldstein, Hasher, & Zacks, 2005), others have found similar effects in both groups (Mayhorn, Fisk, & Whittle, 2002; Rönnlund, Karlsson, Laggnäs, Larsson, & Lindström, 2005), and still others have found a less pronounced framing effect in older adults (Mikels & Reed, 2009; Watanabe & Shibutani, 2010).[1] To the extent that there are age differences in the framing effect, they may reflect a stronger response to option complexity in older than in younger adults.

1.2 | Loss Aversion

In choice problems offering mixed options (i.e., that have both potential gains and losses as outcomes), losses are often thought to receive disproportionate weight ("losses loom larger than gains," Kahneman &

[1]Note that the study by Mikels and Reed (2009) used a monetary gambling task rather than the classic disease problem.

Tversky, 1979, p.279). The tendency to reject the chance to play a gamble offering equal chances of losing and winning equivalent amounts of money (Gächter, Johnson, & Herrmann, 2007; Tom, Fox, Trepel, & Poldrack, 2007) is commonly interpreted as evidence for such loss aversion (for a critical discussion, see Yechiam, 2019). Although the robustness of loss aversion is currently debated,[2] there is a rich literature investigating individual differences in loss aversion (e.g., Gächter et al., 2007; Li, Baldassi, Johnson, & Weber, 2013; Mrkva, Johnson, Gächter, & Herrmann, 2020; Seaman, Green, Shu, & Samanez-Larkin, 2018).

A common approach to measure loss aversion is using lists consisting of several mixed gambles, each offering a 50% chance to gain some amount and a 50% chance to lose some amount (e.g., Gächter et al., 2007). Whereas the gain amount is fixed across gambles, the loss amount varies. People are asked whether they accept or reject the chance to play each gamble. People with stronger loss aversion are expected to reject the gamble more often, even if the gamble's expected value is equal to or greater than zero. Note that such accept/reject choices are essentially choices between a mixed risky gamble and a safe outcome of zero (the consequence of rejecting the gamble). The safe option (rejecting) is considerably less complex than the mixed gamble, which consists of several pieces of numerical information (outcomes and probabilities).

Whereas some studies have found stronger loss aversion in older than in younger adults (Gächter et al., 2007; Mrkva et al., 2020), others have found younger and older adults to be equally loss averse (Li et al., 2013). To the extent that older adults have a stronger preference for the safe option than younger adults, this may reflect older adults' greater sensitivity to differences in complexity between a risky mixed option and a safe alternative, rather than genuine age differences in loss aversion. Consistent with this possibility, in choices between two equally complex risky mixed gambles, Seaman et al. (2018) found no difference in loss aversion between younger and older adults (Pachur, Mata, & Hertwig, 2017, even found lower loss aversion in older than in younger adults in such choice problems).

1.3 | Delay Discounting

How attractive people find options whose outcomes are realized at different points in time is often investigated using choices between a smaller reward that can be obtained immediately (or after a short delay; smaller sooner or SS reward) and a larger reward that can be obtained after a longer delay (larger later or LL reward) (e.g., Dohmen, Falk, Huffman, & Sunde, 2010; Kirby, 2009). Preferring an SS over an LL option in such intertemporal choice tasks indicates delay discounting, that is, discounting a reward's attractiveness as a function of its delay. Delay discounting is particularly pronounced in choices between an immediate and a delayed reward (see Berns, Laibson, & Loewenstein, 2007; McClure, Laibson, Loewenstein, & Cohen, 2004). Similar to a safe outcome in risky choice, an immediate reward in intertemporal choice is comparably simple to evaluate: The decision maker merely needs to consider the reward. An option with a delayed reward, by contrast, is characterized by an additional piece of numerical information—namely, the temporal delay (e.g., a specific number of days). Hence, the decision maker not only has to consider the reward on offer but also whether it is worth waiting the specified amount of time. The availability of an additional attribute (i.e., the delay) may render the evaluation of an option with a delayed outcome more complex than the evaluation of an immediate reward. Such differences in the complexity of options may contribute to delay discounting. Specifically, a preference for an immediate over a delayed reward may reflect not a genuine attitude toward delays, but—to some extent—a response to differences in the complexity of options. Consistent with this possibility, the tendency to choose the SS reward is lower in choices between several delayed rewards—with similar levels of complexity—than in choices between an immediate and a delayed reward (Keren & Roelofsma, 1995).[3]

Findings on age differences in delay discounting are mixed. Some studies have found that older adults discount more than younger adults (Liu et al., 2016; Read & Read, 2004); others have found they discount to a similar degree (Green, Myerson, Lichtman, Rosen, & Fry, 1996; Samanez-Larkin et al., 2011). Others again have found younger adults to discount more than older adults (Eppinger, Nystrom, & Cohen, 2012; Green, Fry, & Myerson, 1994; Green, Myerson, & Ostaszewski, 1999; Li, Baldassi, Johnson, & Weber, 2013; Löckenhoff, O'Donoghue, & Dunning, 2011; Reimers, Maylor, Stewart, & Chater, 2009).

1.4 | Outline Of The Study

We examined the framing effect and loss aversion in risky choice as well as delay discounting in intertemporal choice in younger and older adults using choice tasks that are typically employed to demonstrate these phenomena. We then experimentally increased the complexity of the less complex option (the safe option in the framing and loss aversion tasks and the immediate option in the intertemporal choice task), thus rendering the two options more similar in their complexity. In each case, we investigated whether this manipulation reduced the magnitude of the phenomenon, and whether the degree of any such reduction differed between younger and older adults. We also explored the association between choices in the tasks and self-reports of risk preference, impulsivity, and patience. The study was approved by the IRB of the Max Planck Institute for Human Development Berlin.

[2]For instance, loss aversion has been found to depend on the distribution of gain and loss outcomes (Walasek & Stewart, 2015) and the amount of money at stake (Harinck, Van Dijk, Van Beest, & Mersmann, 2007), as well as other contextual features of the experiment (Ert & Erev, 2013). It has also been proposed that losses may increase attention at task, rather than induce aversion (e.g., Yechiam & Hochman, 2013a, 2013b).

[3]Note that according to our rationale, studies relying on choice problems offering two delayed rewards (e.g., Andersen, Harrison, Lau, & Rutström, 2008; Coller & Williams, 1999; Dai, 2017; Dai & Busemeyer, 2014; Drichoutis & Nayga, 2013; Harrison, Lau, & Williams, 2002) are unlikely to be confounded by differences in option complexity.

2 | METHODS

2.1 | Participants

Eighty younger adults (aged 18–28 years, *M* = 23.9, *SD* = 2.34, 39 female) and 80 older adults (aged 61–77 years, *M* = 70.8, *SD* = 3.83, 40 female) participated in the study. They were recruited via the internal participant data base of the Max Planck Institute for Human Development, Berlin. More detailed information about the participant sample can be found in Table 1. We measured participants' fluid cognitive abilities with the Digit Symbol Substitution Test (DSST; see McLeod, Griffiths, Bigelow, & Yingling, 1982) and their numeracy with the Berlin Numeracy Test (Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero, 2012; see below for a more detailed description of both measures). Nominally, older adults gave, on average, fewer accurate responses on the DSST and scored lower on the numeracy test than younger adults. These findings are consistent with previous research on age differences in cognitive ability measured using these tasks (Hoyer, Stawski, Wasylyshyn, & Verhaeghen, 2004; Pachur et al., 2017; Salthouse, 1992; Tymula, Belmaker, Ruderman, Glimcher, & Levy, 2013; Zilker et al., 2020) and hence indicate that the sample represented typical groups of younger and older adults.

2.2 | Materials

2.2.1 | Framing task

We used five problems with different cover stories (Chick, Reyna, & Corbin, 2016; Rönnlund et al., 2005), including the death of turtles after an oil spill, the destruction of paintings in a burning museum, and the death of civilians in a war region. In each condition, participants were presented with all five problems, framed both positively and negatively.

The problems were presented in each of three conditions. In the *simple safe* condition and the *complex safe* condition, participants made choices between a risky mixed and a safe option. In the simple safe condition, the safe option offered one outcome with certainty, such as "249 turtles will die with certainty." In the complex safe condition, the same safe outcome was presented in a more complex format. This was achieved by expressing the outcome as the sum of two percentages, such as "with certainty, 10% of 20 turtles will die, and with certainty, 90% of 274 turtles will die." In the *risky condition*, participants made choices between two risky mixed options. Each risky mixed option (in all conditions) involved two probabilistic outcomes, such as "with a probability of 10% 20 turtles will die, and with a probability of 90% 274 turtles will die." Note that the numerical properties of this risky mixed option are the same as those of the complex safe option.

In the previous literature, framing problems have often had the same numerical properties (e.g., same number of lives saved/lost) irrespective of the cover story. To avoid such repetition, we constructed problems with distinct numerical properties (stakes and probabilities) for each cover story. The key characteristic of classical framing problems, namely, that both options in each problem have the same expected value (EV), was maintained. The five scenarios involved different total numbers of persons/objects at stake (100, 300, 500, 700, or 900). In all conditions, each scenario involved one risky option, constructed as follows: The two outcomes of the risky option were set to the total number of objects at stake and to zero, respectively. The probability of the first risky outcome was uniformly drawn from 0.01 to 0.99; the probability of the second risky outcome was set to the complementary probability.

In the simple safe condition, this risky option was paired with a safe outcome. The magnitude of the safe outcome in the positive (negative) frame was obtained by multiplying the probability of all objects being saved (lost) in the risky option by the total number of objects at stake in the respective scenario. This ensured that both options had equal EVs.

TABLE 1 Characteristics of the participant sample: Cognitive measures, self-report measures, and amount of the bonus obtained in the loss aversion task

	Younger adults			Older adults		
	M	(SD)	[min; max]	M	(SD)	[min; max]
Age (in years)	23.9	(2.34)	[18; 28]	70.8	(3.83)	[61; 77]
DSST						
Prop. acc. responses	0.96	(0.03)	[0.83; 1]	0.97	(0.03)	[0.86; 1]
No. acc. responses	57.38	(9.41)	[32; 84]	37.19	(6.88)	[24; 56]
Numeracy score	4.01	(1.78)	[1; 7]	2.51	(1.47)	[0; 6]
Self-report measures						
Risk preference	5.16	(1.97)	[1; 8]	4.81	(1.87)	[1; 9]
Impulsivity	4.8	(2.11)	[0; 9]	5.13	(1.96)	[0; 10]
Patience	5.5	(2.6)	[0; 10]	6.15	(2.13)	[0; 10]
Bonus in loss aversion task (in EUR)	3.7	(1.81)	[1; 8]	3.53	(1.71)	[0; 7]

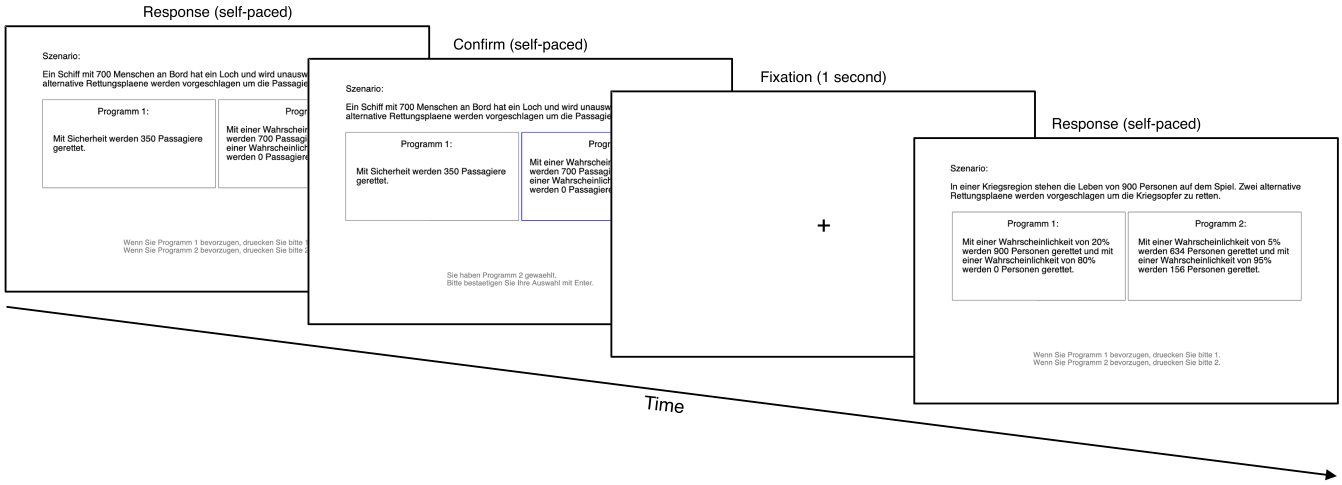

FIGURE 1 Timeline of the framing task with sample choice problems. Participants made self-paced choices, confirmed those choices by pressing the enter key, and moved on to the next scenario after a fixation period of 1 second [Color figure can be viewed at wileyonlinelibrary.com]

In the risky condition, the original risky option was paired with a second risky option. To obtain this second risky option, the probability of the first risky outcome was uniformly drawn from 0.01 to 0.99, and the probability of the second risky outcome was set to the complementary probability. The first risky outcome was uniformly drawn from 10 to the total number of objects at stake in the respective scenario. The second outcome was calculated such that the combination of outcomes and probabilities matched the EV of the original risky option.

The numerical features of the second risky option were also used to construct the complex safe option for the complex safe condition. Here, the probabilities were used as proportions. For instance, a risky option reading "with a probability of 10%, 20 turtles will die, and with a probability of 90%, 274 turtles will die" would correspond to a complex safe option reading "with certainty, 10% of 20 turtles will die, and with certainty, 90% of 274 turtles will die."

Because individual scenarios were presented repeatedly in different formats and frames (two frames × three conditions), we split the framing trials into two blocks. One block was presented at the beginning of the experiment, followed by the loss aversion task and the intertemporal choice task, and then the second block of framing trials. Which version of each choice problem appeared in the first or second block was determined in a pseudorandom manner for each participant individually, ensuring that half of the total six versions of each scenario (two frames × three conditions) were presented in each block. The order of scenarios within each block was randomized for each participant individually, as was the side of the screen on which the options within each trial were presented. Participants were instructed to read each scenario and its options carefully, even if they appeared very similar. They were informed that individual scenarios always differed in important respects. Participants were also instructed to pay close attention to whether percentages (which appeared in both complex safe and risky options) referred to proportions or probabilities. Participants made choices by pressing Keys 1 and 2, corresponding to the options ("Programs 1 and 2") on each trial. Figure 1 shows the timeline of the framing task with sample choice problems.

2.2.2 | Loss aversion task

We also constructed a loss aversion task with three conditions. Each condition (*simple safe*, *complex safe*, and *risky*) consisted of 21 choices, amounting to 63 choices overall. All conditions involved choices between a risky mixed gamble and an alternative option. The alternative option was either a simple safe, a complex safe, or a risky mixed option (depending on condition).

The numerical structure of the choice problems was constructed on the basis of the choice list by Gächter et al. (2007).[4] Each pair consisted of a safe option and a risky mixed option. Safe options offered an amount of zero, while risky mixed options offered two outcomes, each with a probability of 50%; one outcome was always 6 and the other varied across trials (possible values being −3, −4, −5, −6, −7, −8, and −9). In this regard, we slightly modified the choice list of Gächter et al., such that the safe option was the better choice in the same number of problems as the risky option. This ensured that across problems, differences in risk between options were independent of differences in EV. Loss aversion is indicated by a tendency to choose the safe option even if the EV of the risky option (which includes potential loss outcomes) is greater than zero. This is because under loss aversion, the risky gain has to be larger than the equiprobable risky loss to outweigh the greater impact of the possible loss.

We manipulated the complexity of the safe outcome. Specifically, in the simple safe condition, people made choices between a risky mixed gamble and a simple safe amount (e.g., 100% chance to win 0).

[4]The amounts of potential gains and losses in our task are also comparable to those used by, for instance, Mrkva et al. (2020) and Sheng et al. (2020).

In the complex safe condition, people made choices between a risky mixed gamble and a complex safe amount. As in Zilker et al. (2020), the safe option offered the same outcome magnitude as in the simple safe condition. However, this outcome was now expressed as a mathematical term in which two integers had to be multiplied by .5 and one then subtracted from the other. For instance, a safe outcome of −3 could be expressed as a 100% chance to win $(0.5 \times 2) - (0.5 \times 8)$. We also included a risky condition, which involved choices between two mixed gambles (of similar complexity).

In the risky condition, one of the options in each choice problem was based on the risky mixed gambles also used in the other two conditions. The second was a new risky mixed gamble, offering each outcome with a chance of 50%. These gambles were numerically analogous to the complex safe options in the corresponding choice problems of the complex safe condition. For instance, if a complex safe option offered a 100% chance to win $(0.5 \times 2) - (0.5 \times 8)$, the second risky gamble in the corresponding choice problem of the risky condition offered a 50% chance to win 2 and a 50% chance to win 8. This ensured that the options' EVs were matched across conditions.

In the simple safe condition and the complex safe condition, we added distractor trials, which required a choice between a mixed risky option and a safe positive or negative outcome (with EVs unequal to zero, either −3 or +3). The risky mixed options for distractor trials were the same as those on the original choice list by Gächter et al. (2007). We added these distractor trials for the following reason: Had the safe option been zero in all choice problems, participants would have been able to infer the value of the complex safe option without computing the mathematical terms, jeopardizing the complexity manipulation. Both the simple safe condition and the complex safe condition involved 14 such distractor problems (7 with positive and 7 with negative safe options). In the complex safe condition, the safe distractor outcome was displayed as a mathematical term.

The order of presenting the choice problems was randomized uniquely for each participant. All outcomes were presented in the experimental currency $. Participants were informed that they could obtain between 0 and 10 Euros in potential bonus payments (see below for details). Participants made choices by pressing Keys F and J, corresponding to the left and right option on screen, respectively. Figure 2 shows the timeline of the loss aversion task with sample choice problems.

2.2.3 | Intertemporal choice task

We also constructed an intertemporal choice task with three conditions. Each condition involved choices between a smaller sooner (SS) and a larger later (LL) reward. In the *simple immediate* condition, the choice problems consisted of a simple smaller immediate and a larger delayed reward, such as $5 today versus $10 in 15 days. In the *complex immediate* condition, the complexity of the smaller immediate amount was increased by expressing it as a mathematical term, requiring an amount to be multiplied by a decimal number. For instance, an immediate reward of $1 in the simple immediate condition might be described as (0.25×4) in the complex immediate condition. In the *delayed condition*, both the SS and the LL reward were delayed.

The numerical features of the choice problems were constructed as follows. Ten SS reward amounts were randomly drawn from a uniform distribution ranging between 10 and 200. For each SS reward, we then generated an LL reward by increasing the SS rewards by a proportion of the SS amount, evenly spaced between .1 and .8. The resulting 10 pairs of SS and LL rewards were used in all three conditions. To make it less recognizable that the same options recurred across conditions, the SS rewards used in the simple immediate condition were jittered by ±1 in the two other conditions. For instance, if 1 was added to the original SS reward in the complex immediate condition, then 1 was subtracted from the original SS reward in the delayed condition, and vice versa. For each trial, it was randomly determined in which condition the reward was positively or negatively jittered.

The delays associated with these rewards were generated as follows. In the immediate condition, the SS reward was realized "today." In the delayed condition, the SS reward was always delayed

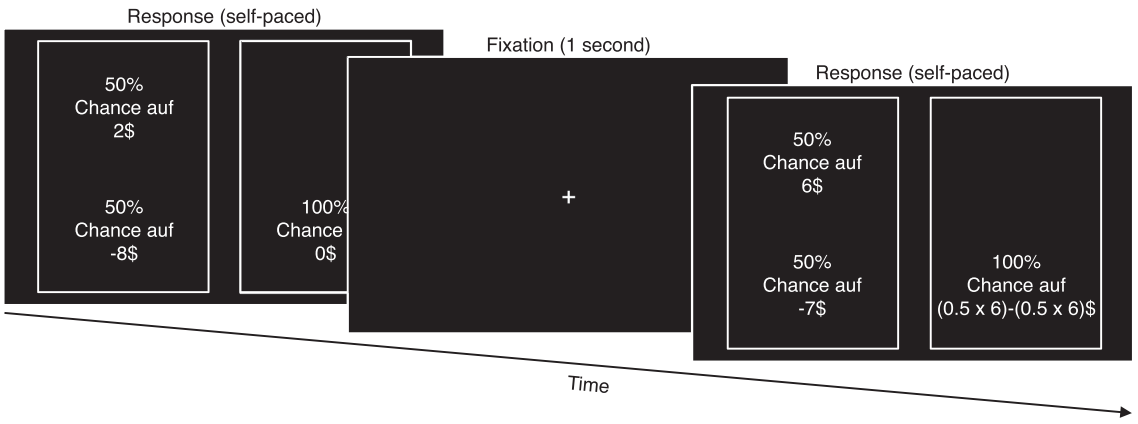

FIGURE 2 Timeline of the loss aversion task with sample choice problems. Participants made self-paced choices, beginning the next trial after a fixation period of 1 second

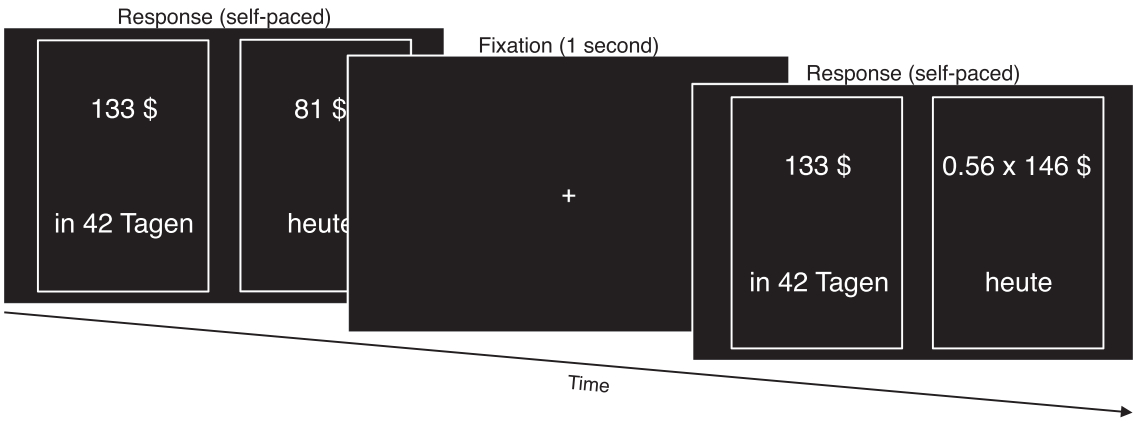

FIGURE 3 Timeline of the intertemporal choice task with sample choice problems. Participants made self-paced choices, beginning the next task after a fixation period of 1 second

by 14 days. The delays associated with the LL rewards were generated as follows. In each condition there were three possible delays for each LL reward (14, 28, or 42 days after the corresponding SS option).[5] That is, in each condition, each of the 10 pairs of reward amounts was presented with three possible delays, resulting in 30 choices per condition and 90 choices in total. The procedure for generating the stimuli thus ensured that the choice problems covered a broad range of reward values and delay durations.

In order to assess participants' attentiveness while working on the task, we included six attention-check trials in each condition. Here, participants made choices between a larger sooner and a *smaller* later amount: The larger sooner amount was the dominant option, offering both a larger reward and a sooner time of provision.

All outcomes were presented in the experimental currency $. Participants indicated their choices by pressing Keys F and J, corresponding to the left and right option on the screen, respectively. The order of trials was randomized individually for each participant, as was the side of the screen on which the options within each trial were presented. Figure 3 shows the timeline of the framing task with sample choice problems.

2.2.4 | Additional measures

We administered several cognitive and self-report measures to further characterize the sample. Participants completed the seven-item version of the *Berlin Numeracy Test* (Cokely et al., 2012), to measure their ability to understand operations of probabilistic computation, and the *Digit Symbol Substitution Test* (DSST; for details, see McLeod et al., 1982), an approximate measure of fluid intelligence in terms of speed of processing. Results are summarized in Table 1. Participants were also asked to indicate their self-reported risk preference on a one-item general risk question (a higher value indicates a higher propensity to take risks; Dohmen et al., 2011) and to self-report their impulsivity and patience on standard items from the German Socio-Economic Panel (SOEP; see Richter, Metzing, Weinhardt, & Schupp, 2013) with an 11-point response scale (see the supporting information for details).

2.3 | Procedure

Participants received a baseline payment of €20 for participating in the experiment, and a performance-contingent bonus ranging between €0 and €10, depending on their responses in the loss aversion task.[6] Before the beginning of the experiment, the experimenter put €5 on the desk in front of the participant as a baseline bonus. The experimenter explained that the participant's choices in the experiment would determine whether they would get to keep this baseline bonus and possibly increase it up to €10 or have to return part or all of it. In the loss aversion task, more detailed instructions on how bonuses were calculated were provided in written form. At the end of the loss aversion task, one trial was randomly selected, and the option chosen by the participant was played out. The resulting outcome was converted from the experimental currency $ into € and added to or subtracted from the baseline bonus of €5.[7]

The experiment started with a first block of the framing task, followed by the loss aversion task and the intertemporal choice task—the order of presentation of which was randomized individually for

[5]The possible delays for LL rewards in the two conditions with immediate rewards were thus "in 14 days," "in 28 days," and "in 42 days"; the corresponding delays for the delayed condition were "in 28 days," "in 42 days," and "in 56 days."

[6]Bonus payments were only given on the loss aversion task for the following reasons: Any bonus payments in the intertemporal choice task would have to have been paid out after a time delay. This would have required either inviting participants back to the institute to collect their bonus or gathering their bank account details to make a transfer. We decided against this procedure because the effort of returning to the institute would likely have outweighed the benefit of collecting a (relatively small) bonus and for data protection reasons. The outcomes of the framing task (e.g., "200 turtles will die") do not naturally lend themselves to being implemented as a bonus. An incentivization based on the chosen options' EV in the framing task would not have been meaningful either, given that each choice problem involved two options with equal EVs.

[7]For the conversion, the played out reward in the experimental currency was multiplied by 0.4 to ensure that the total bonus (including the baseline bonus of €5) remained within the target range €0 to €10.

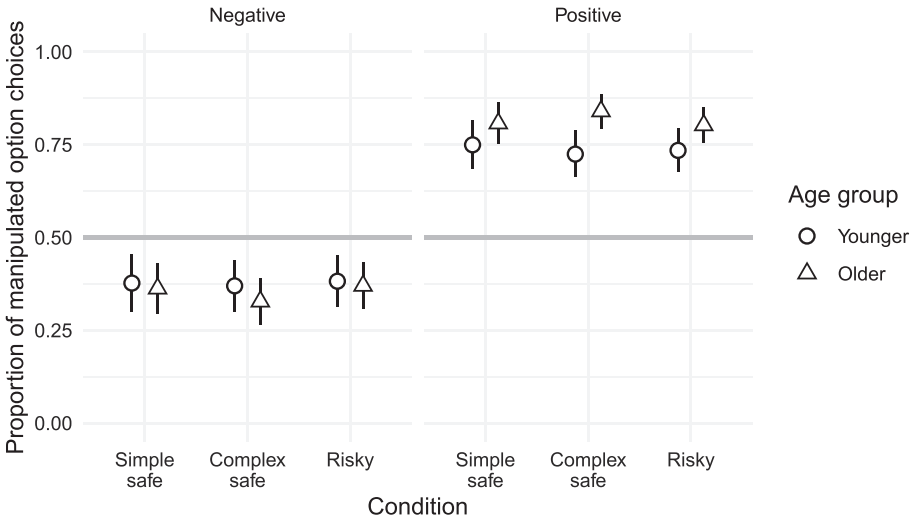

FIGURE 4 Choice proportions of the manipulated option (the safe option in the simple safe and complex safe condition; the second risky option in the risky condition) in the framing task, for problems presented with negative framing (left panel) and positive framing (right panel). Error bars indicate 95% confidence intervals

each participant—and the second block of the framing task. The three main tasks were followed by the Berlin Numeracy Test, the DSST, and the self-report measures of risk preference, impulsivity, and patience. Finally, participants were asked to indicate their age and sex and given the opportunity to comment on the experiment in an open text format. Then, the experimenter revealed the result of the automatically determined random bonus gamble and paid the participant.

3 | RESULTS

All behavioral analyses were performed in RStudio (Version 1.2.5033). All Bayesian generalized linear mixed model (GLMM) analyses reported below were implemented using the rstanarm package (Goodrich, Gabry, Ali, & Brilleman, 2018). Individual effects in GLMMs were considered credible if the 95% posterior interval for the coefficient excluded zero.

When reporting the effects of the factor "condition" (which has three levels in each choice domain), we use the simple condition as the reference condition unless specified otherwise and indicate the condition compared with it in brackets. For instance, in the loss aversion task, a main effect of condition (complex safe) refers to the comparison between the simple safe and the complex safe condition—the effect of complexity. An interaction between condition (complex safe) and age group (older) describes whether the difference between the simple safe and the complex safe condition differs between older and younger adults (e.g., whether older adults showed a stronger response to complexity). For the factor "age group," the younger adults served as the reference. All models included a random intercept for each participant.

3.1 | Manipulation checks

As in Zilker et al. (2020), we first checked whether the complexity manipulation was successful by inspecting response times (RTs) and decision quality (the tendency to choose the option with the higher EV). In both the loss aversion task and the dominated trials of the intertemporal choice task, the complexity manipulation negatively affected decision quality. Overall, the decision quality observed in both tasks and across conditions was relatively high, indicating that participants understood the options, even in the more complex format. In the framing task, decision quality cannot be assessed, as both options have equal EVs. Across all choice tasks, the complexity manipulation was associated with longer RTs, suggesting that participants carefully engaged with the task also in the more complex conditions. These results echo similar findings of Zilker et al. (2020) and indicate that the complexity manipulation successfully increased the complexity of the typically simpler option. Full analyses on RTs and decision quality are reported in the supporting information.

3.2 | Framing task

As shown in Figure 4, there was a pronounced framing effect, such that participants predominantly chose the risky option in the negative frame and the safe option in the positive frame. This held for both age groups and across all conditions. More specifically, in the simple safe condition, participants chose the safe option in, on average, 78% of cases in the positive frame (75% in younger adults, YA; 81% in older adults, OA) and 37% of cases in the negative frame (38% YA; 36% OA). In the complex safe condition, participants chose the safe option in, on average, 78% of cases in the positive frame (72% YA; 84% OA) and 35% of cases in the negative frame (37% YA; 33% OA). In the risky condition, participants chose the second risky option in, on average, 77% of cases in the positive frame (74% YA; 80% OA) and 38% of cases in the negative frame (38% YA; 37% OA).

To quantify the size of the framing effect, we calculated a framing index. The index expresses the extent to which participants chose different options across frames (e.g., the safe option in the positive frame, but the risky option in the negative frame of the same scenario in a given complexity condition). The framing index is 0 if a participant

chose the same option across frames, and 1 if their choices differed across frames. Figure 5 shows the framing index in each complexity condition, separately for younger and older adults. To examine whether there were age differences in the size of the framing effect at baseline—that is, in the simple safe condition—we calculated a Bayesian logistic GLMM with the framing index as the dependent variable and age group as a fixed effect. There was no credible age difference in the framing effect in the simple safe condition ($\beta_{agegroup}$ = 0.37, 95% *PI* [−0.09, 0.83].)

We next tested whether the magnitude of the framing effect was affected when the safe option was displayed in a more complex format. To this end, we calculated Bayesian logistic GLMMs with the framing index as the dependent variable and complexity condition as a fixed effect. This model was calculated separately for each age group. As Table 2 shows, the effects of condition were not credible in either age group. That is, the magnitude of the framing effect was not affected by the complexity manipulation, in either age group.

Finally, we tested for an interaction between age group and condition on the framing effect. We calculated a Bayesian logistic GLMM with the framing index as the dependent variable and fixed effects for age group and condition, as well as the interaction between age group and condition. As Table 3 shows, neither the interaction between age group and condition (complex safe) nor the interaction between age group and condition (risky) was credible. That is, the impact of the complexity manipulation on the size of the framing effect did not differ between younger and older adults.

In summary, we found no evidence that the framing effect was driven by the differences in option complexity in the typically used choice task; likewise, we found no evidence for a stronger response to option complexity in older than in younger adults in the framing task.

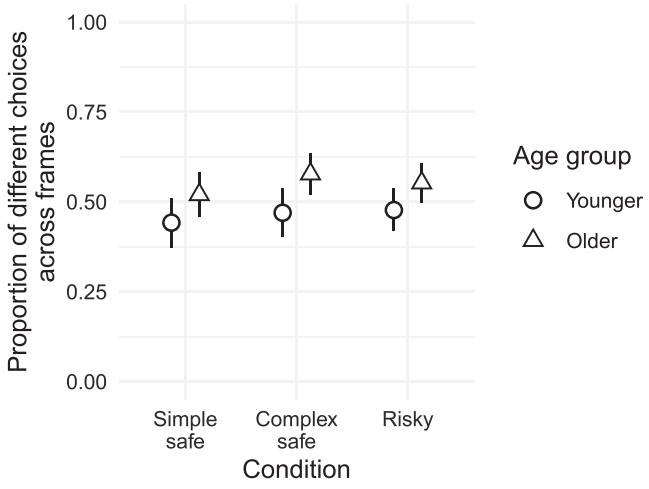

FIGURE 5 Proportion of trials in which participants chose different options across the positive and negative frames—that is, in which they reversed their preferences depending on framing. Error bars indicate 95% confidence intervals

TABLE 2 Coefficients and 95% posterior intervals for the Bayesian logistic GLMMs for effects of the complexity manipulation on the framing effect, by age group

Predictor	Younger	Older
(Intercept)	−0.3 [−0.63, 0.02]	0.08 [−0.16, 0.34]
Condition (complex safe)	0.13 [−0.16, 0.45]	0.26 [−0.03, 0.53]
Condition (risky)	0.17 [−0.14, 0.49]	0.15 [−0.14, 0.42]

Note. Dependent variable: different choice across frames.

TABLE 3 Coefficients and 95% posterior intervals for the Bayesian logistic GLMMs for interaction effects of age group and complexity manipulation on the framing effect

Predictor	
(Intercept)	−0.29 [−0.58, 0.01]
Age group (older)	0.37 [−0.03, 0.79]
Condition (complex safe)	0.13 [−0.16, 0.44]
Condition (risky)	0.18 [−0.13, 0.46]
Age group (older) × condition (complex safe)	0.14 [−0.29, 0.53]
Age group (older) × condition (risky)	−0.02 [−0.44, 0.39]

Note. Dependent variable: different choice across frames.

3.3 | Loss aversion task

Figure 6 shows the proportion of choices of the safe option in nondistractor trials of the loss aversion task as a function of the complexity of the safe option and the EV of the alternative risky option. To recap, in all nondistractor trials the safe option had a value of zero. The tendency to choose the safe option—which ensures the avoidance of losses—can be used as a measure of loss aversion. Both younger and older adults chose the safe option in, on average, 44% of cases in the simple safe condition and in 42% of cases in the complex safe condition. These choice proportions indicate that participants were not loss averse. Nominally, there was even a slight preference for the risky option, indicating gain seeking rather than loss aversion. We further address this pattern in the General Discussion (section 8). In the risky condition, participants chose the second risky option in, on average, 51% of cases (50% OA; 52% YA).

We next tested whether there were age differences in the tendency to choose the safe option (i.e., the option that would avoid a loss for sure) in the simple safe (i.e., baseline) condition. To this end, we calculated a Bayesian logistic GLMM with choice of the safe option as the dependent variable and fixed effects for age group, the EV difference $EV_{risky} - EV_{safe}$, and each participant's self-reported risk preference. There was no credible main effect of age group ($\beta_{agegroup}$ = −0.07, 95% *PI* [−0.98, 0.86]). Both EV difference ($\beta_{EV\ diff}$ = −1.75, 95% *PI* [−2, −1.51]) and self-reported risk preference had a credible effect ($\beta_{self\ report\ risk}$ = −0.28, 95% *PI* [−0.52, −0.04]). We thus found no evidence for differences in loss aversion between younger and older adults.

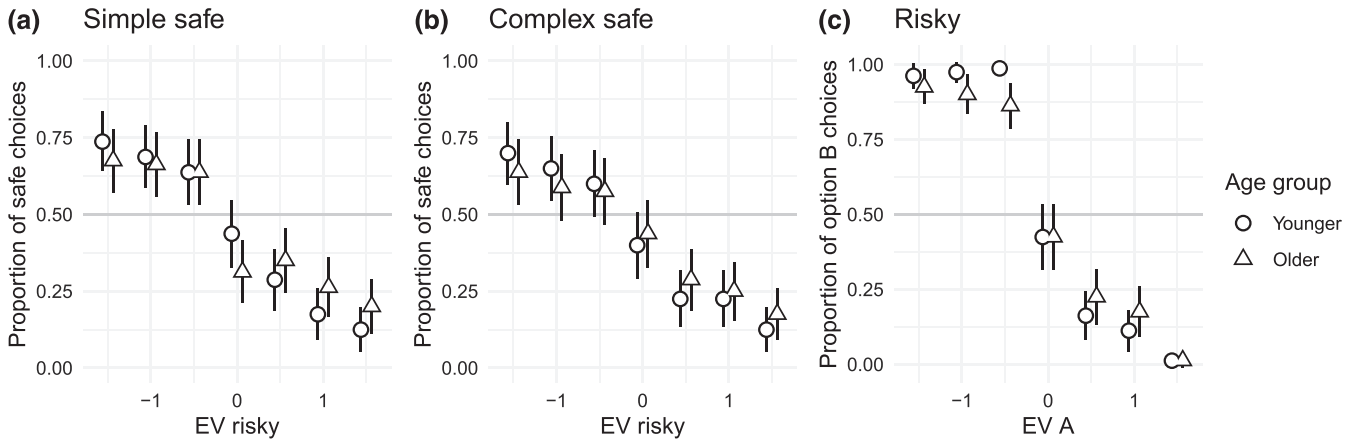

FIGURE 6 Choice proportions of the manipulated option in the loss aversion task, in the (a) simple safe, (b) complex safe, and (c) risky conditions and by age group

To test for potential effects of option complexity, we next calculated Bayesian logistic GLMMs with the choice of the manipulated option (i.e., the simple safe option, the complex safe option, or the second risky option, depending on condition) as the dependent variable, including fixed effects for age group, complexity condition, the EV difference $EV_{risky} - EV_{safe}$ (in the risky condition $EV_{risky} - EV_{manipulated}$), and self-reported risk preference (main effect model). To test whether the effect of option complexity on the tendency to choose safe options differed between age groups, we also calculated an interaction model that included the interaction between the complexity condition and age group as a fixed effect. Results are reported in Table 4. As can be seen, there was no credible main effect of condition (complex safe) on the tendency to choose the manipulated (safe) option. Moreover, there was no credible main effect of age group, indicating that younger and older adults were similarly likely to choose the manipulated option. A credible positive main effect of condition (risky) indicates that in choices between two risky options (both involving the possibility of a loss), participants were more likely to choose the manipulated option (i.e., new risky mixed gamble; see section 6). A negative effect of EV difference on the tendency to choose the manipulated option indicates that participants were less likely to choose this option if the (nonmanipulated) risky option had a higher EV. The interaction model further showed that there were no credible interactions between age group and condition, indicating that the age groups did not differ in their response to the complexity manipulation.

In sum, preferences in a task typically thought to measure loss aversion were not affected by differences in the complexity the options. In fact, we did not find loss aversion in either condition. Moreover, in terms of their tendency to choose the safe option, younger and older adults did not differ in their response to complexity differences.

TABLE 4 Coefficients and 95% posterior intervals for the Bayesian logistic GLMMs for the choices in the loss aversion task (nondistractor trials)

Predictor	Main effect model	Interaction model
(Intercept)	0.27 [−0.38, 0.9]	0.25 [−0.41, 0.89]
Age group (older)	−0.07 [−0.49, 0.34]	−0.04 [−0.53, 0.43]
Condition (complex safe)	−0.15 [−0.36, 0.07]	−0.16 [−0.47, 0.14]
Condition (risky)	**0.51 [0.28, 0.72]**	**0.54 [0.24, 0.85]**
EV difference	**−1.58 [−1.7, −1.46]**	**−1.58 [−1.7, −1.46]**
Self-reported risk preference	**−0.13 [−0.24, −0.02]**	**−0.13 [−0.23, −0.02]**
Age group (older) × condition (complex safe)		0.04 [−0.4, 0.49]
Age group (older) × condition (risky)		−0.07 [−0.51, 0.36]

Note. Dependent variable: manipulated option choice. Boldface indicates credible effects.

3.4 | Intertemporal choice task

In intertemporal choice problems with dominated options, participants predominantly chose the dominant (larger sooner) option, suggesting that they worked on the task attentively. Details are reported in the supporting information.

Figure 7 shows choice behavior in the nondominated trials (where the sooner reward was smaller than the later reward). Across these trials, participants choose the SS option in, on average, 40% of cases. Participants chose the immediate option in, on average, 41% of cases in the simple immediate condition (42% OA; 39% YA) and 39% of cases (42% OA; 36% YA) in the complex immediate condition. In the delayed condition, where participants chose between two delayed options, the sooner option was preferred in, on average, 42% of cases (44% OA; 40% YA).

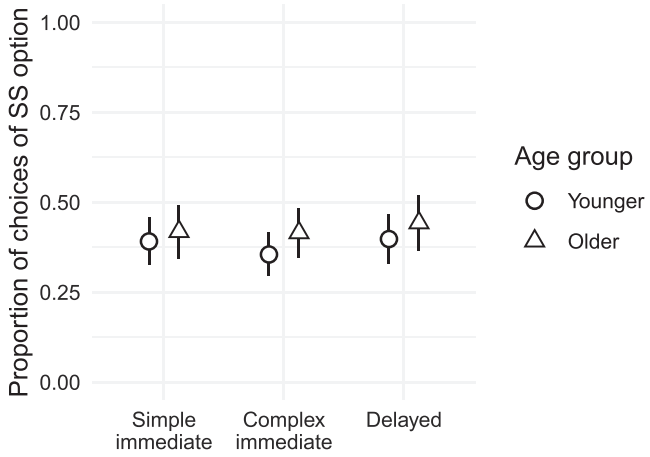

FIGURE 7 Choice proportions of the smaller sooner (SS) option in the three conditions of the intertemporal choice task. Error bars indicate 95% confidence intervals

We next tested whether younger and older adults differed in their tendency to choose the SS option in the simple immediate condition. We calculated a Bayesian GLMM with choice of the SS (here simple immediate) option as the dependent variable, and fixed effects for age group and self-reports on patience and impulsivity. Coefficients and 95% posterior intervals are reported in Table 5. There was no credible effect of age group on the tendency to choose the immediate option ($\beta_{agegroup}$ = 0.15; 95% *PI* [−0.53, 0.85]). Self-reported impulsivity had a positive and credible effect ($\beta_{impulsivity}$ = 0.26; 95% *PI* [0.08, 0.44]) on choice of the immediate option; self-reported patience was not related to choosing the immediate option ($\beta_{patience}$ = 0.03; 95% *PI* [−0.13, 0.18]).

To test whether reducing complexity differences between the options (by increasing the complexity of the immediate reward) affected the tendency to choose the immediate reward, we calculated Bayesian GLMMs with choice of the SS option as the dependent variable and fixed effects for condition and self-reports on patience and impulsivity. This model was estimated separately for each age group. Coefficients and 95% posterior intervals are displayed in Table 6. Increasing the complexity of the immediate reward decreased younger adults' tendency to choose it but did not affect older adults' choices. That is, attenuating differences in option complexity reduced delay discounting in younger but not in older adults. This finding was corroborated by an additional model combining the data from both age groups, which further included the interaction between condition and age group. There was a credible interaction between age group (older) and condition (complex immediate), indicating that the age groups responded differently to an increase in the complexity of the immediate reward (Table 7).

To summarize, younger but not older adults were less likely to choose the immediate over the delayed option when it was displayed in a more complex format, compared to the baseline version of the task. The direction of age differences in the effect of option complexity in this task is thus opposite to that observed for risky choice by Zilker et al. (2020).

4 | GENERAL DISCUSSION

Zilker et al. (2020) demonstrated that choices between a safe and a risky option—often used to measure people's risk attitudes—are

TABLE 5 Coefficients and 95% posterior intervals for the Bayesian logistic GLMMs for responses in the intertemporal choice task (simple immediate condition)

Predictor	
(Intercept)	**−2.06 [−3.57, −0.59]**
Age group (older)	0.15 [−0.53, 0.85]
Self-reported patience	0.03 [−0.13, 0.18]
Self-reported impulsivity	**0.26 [0.08, 0.44]**

Note. Dependent variable: choice of smaller sooner option in simple immediate condition. Boldface indicates credible effects.

TABLE 6 Coefficients and 95% posterior intervals for the Bayesian logistic GLMMs for responses on the intertemporal choice task, by age group

Predictor	Younger	Older
(Intercept)	**−1.96 [−3.64, −0.16]**	−1.71 [−3.83, 0.58]
Condition (complex immediate)	**−0.24 [−0.39, −0.1]**	0.02 [−0.14, 0.17]
Condition (delayed)	0.04 [−0.1, 0.18]	0.13 [−0.02, 0.29]
Self-reported patience	−0.02 [−0.2, 0.16]	0.05 [−0.18, 0.3]
Self-reported impulsivity	**0.3 [0.07, 0.52]**	0.19 [−0.06, 0.45]

Note. Dependent variable: choice of smaller sooner option. Boldface indicates credible effects.

TABLE 7 Coefficients and 95% posterior intervals for the Bayesian logistic GLMMs for responses on the intertemporal choice task

Predictor	
(Intercept)	**−1.84 [−3.32, −0.49]**
Age group (older)	0.15 [−0.42, 0.81]
Condition (complex immediate)	−0.24 [−0.39, −0.1]
Condition (delayed)	0.04 [−0.1, 0.18]
Self-reported patience	0 [−0.13, 0.14]
Self-reported impulsivity	**0.25 [0.09, 0.42]**
Age group (older) x condition (complex immediate)	**0.26 [0.06, 0.47]**
Age group (older) x condition (delayed)	0.1 [−0.11, 0.3]

Note. Dependent variable: choice of smaller sooner option. Boldface indicates credible effects.

substantially influenced by differences in the complexity of the options available. In particular, older adults' more pronounced tendency to choose the safe option in the gain domain emerged to be driven by differences in option complexity, rather than reflecting genuine age differences in risk attitude. Several other prominent phenomena in decision making are also typically demonstrated in paradigms in which a structurally simpler option is paired with a more complex option, raising the question of whether differences in option complexity also contribute to these phenomena, and to age differences therein. In this article, we examined this possibility for the framing effect and loss aversion in risky choice, and for delay discounting in intertemporal choice.

The results provided little evidence that preferences in these tasks are driven by differences in option complexity. Experimentally reducing differences in option complexity did not affect the magnitude of the framing effect nor did it affect the tendency to choose a safe outcome of zero over a mixed gamble—which is typically interpreted as an indicator of loss aversion. We also found no evidence for age differences in the response to option complexity in the choices. Increasing the complexity of the immediate reward in the intertemporal choice task made younger but not older adults less likely to choose the immediate reward. This may raise questions about the replicability of the earlier findings of age differences in the response to option complexity in risky choice Zilker et al. (2020). Notably, these effects have already been replicated in two independent participant samples and settings by Zilker et al. (2020). Moreover, the current study replicates the effects of option complexity on decision quality and response times, also observed in Zilker et al. (2020). This points toward the robustness of the original findings (which may be further assessed in independent replications).

In the following, we relate our present results to previous findings on conditions under which effects of differences in option complexity may (not) manifest.

4.1 | When might preferences be unaffected by differences in option complexity?

4.1.1 | Risky options with zero outcomes

Zilker et al. (2020) observed main effects of option complexity and interactions with age group in choices between safe options and risky options with two nonzero outcomes, but these effects were attenuated when the risky option had one outcome of zero. Because risky outcomes of zero can be ignored, they render complexity differences between the options smaller than in choices between a safe and a risky option with two nonzero outcomes. Notably, in the framing task, one of the outcomes of the risky option is also always zero—for instance "with a probability of 80%, 900 people will die and with a probability of 20%, 0 people will die." This may explain—admittedly post hoc—why the complexity manipulation did not affect preferences in the framing task and why younger and older adults behaved very similarly.

4.1.2 | Tasks involving losses

Moreover, in the experiments by Zilker et al. (2020), option complexity affected risky choice behavior (and age differences therein) primarily in the gain domain and substantially less in the loss domain. Both the framing task and the loss aversion task in the current study also offered loss outcomes. Why might the presence of losses diminish an impact of option complexity? There is evidence that the prospect of a loss increases the effort invested in processing information about the options—that is, decision makers try harder to identify and choose the better option (e.g., Lejarraga & Hertwig, 2017; Yechiam & Hochman, 2013a). The overall very high level of choices of the better option (in terms of EV) in the loss aversion task (see the supporting information) suggests that such an effect may also have been present in the current study. In the framing task, an analysis of RT data (see the supporting information) showed that older adults' RTs were generally longer in the negative than in the positive frame, indicating a greater cognitive investment in choices involving the possibility of losses. Moreover, in both age groups, increasing the complexity of safe options entailed a stronger increase in RTs in the loss domain than in the gain domain. This finding further suggests that participants were especially motivated to perform well on the challenging, complex choice problems when the outcomes were framed as losses, possibly counteracting an effect of option complexity.

4.1.3 | Choice difficulty

It is possible that younger and older adults barely differed in their response to option complexity in the present study because task difficulty was relatively low—as indicated by very high levels of decision quality in both the loss aversion task and the dominated trials of the

intertemporal choice task, even when the options were shown in the more complex format (see the supporting information). The loss aversion task is relatively simple because all probabilities and decimals are either 1, 0, or .5 and rewards consist of single-digit numbers. By contrast, the risky choice problems used by Zilker et al. (2020) involved more diverse probabilities and rewards sampled from the range 1 to 100. Note that it is not possible to assess decision quality in the framing task, because both options on each trial had equal EVs.

It has previously been shown that age differences between younger and older adults emerge primarily when the (cognitive) task demands are relatively high. For instance, a meta-analysis on risky choice concluded that there were age differences only in paradigms with high learning requirements (Mata, Josef, Samanez-Larkin, & Hertwig, 2011). Hence, the finding that older adults did not respond more strongly than younger adults to option complexity in the tasks investigated here may be due to the low difficulty levels of the choice problems, which allowed participants from both age groups to identify a preferable option relatively easily.

Age differences in the response to option complexity might still emerge in more difficult tasks. Although option complexity might have a stronger effect on age differences in tasks with higher difficulty, note that the tasks we used are similar to those commonly used in the literature (e.g., Gächter et al., 2007; Kim et al., 2005). Thus—regardless of the low difficulty of the choice problems—our findings are informative for one of our key question, namely, whether option complexity might have contributed to previous observations of age differences on such tasks.

4.2 | Differences in option complexity in intertemporal choice

We posited that immediate and delayed rewards might differ in complexity because the delayed option requires the delay to be taken into account as an additional attribute, whereas the immediate option can be evaluated at face value. These differences in option complexity in commonly used intertemporal choice tasks may be relatively small compared with those in risky choice problems, where older adults have been found to be more sensitive to complexity (see Zilker et al., 2020). The magnitude of complexity differences in intertemporal choice may, instead, be comparable to that in risky choice problems involving outcomes of zero. Here, too, both options consist of only one nonzero reward, and the risky option requires evaluation of an additional attribute: the probability of the nonzero outcome. The probability of the (thus simpler) safe option can be disregarded—akin to the delivery time of immediate rewards. Crucially, in such risky choice problems, Zilker et al. (2020) did not find older adults to be more sensitive to differences in option complexity than younger adults. Relatively small differences in complexity observed between immediate and delayed options in the baseline condition (simple immediate) may therefore explain why there were no credible differences between younger and older adults' choices in this condition, and why older adults did not show a stronger response to the complexity manipulation than younger adults.

Nevertheless, one curious finding remains unexplained. Increasing the complexity of the immediate reward made younger, but not older, adults less likely to choose these options. That is, in contrast to previous findings for risky choice (Zilker et al., 2020), younger rather than older adults appeared to be more sensitive to option complexity. Notably, time preferences represent a different domain than risk preferences, and this might contribute to the differences. However, it is currently unclear why complexity differences might play out differently in different domains; this disparity should be addressed in future research, including replications of the current experiments.

4.3 | The fragility of loss aversion

Participants did not display loss aversion in our loss aversion task—in fact, choice proportions indicated a slight preference for the risky option, which involved a potential loss. Several factors may have contributed to this perhaps surprising result. First, our task involved explicit choices between two options. Ert and Erev (2008) showed that decision makers were averse to mixed gambles—indicating loss aversion—when asked to accept or reject them (the task format used, for instance, by Gächter et al., 2007; Tom et al., 2007), but not when asked to choose between a mixed gamble and a sure outcome of zero. Second, our task involved rather low outcomes. Ert and Erev (2013) found low levels of loss aversion when the stakes were rather low (but note that Gächter et al. found clear evidence for loss aversion with stimuli that involved similarly low outcomes as in our study). Harinck et al. (2007) even reported a reversal of loss aversion—that is, gain seeking—for tasks involving options with low stakes; loss aversion appeared only in problems with higher stakes. Third, loss aversion has been shown to disappear in balanced choice sets, where the better choice is a risky option as often as it is a safe option (Ert & Erev, 2013). The set of choice problems used in our experiment was balanced in this regard. Although our participants did not display loss aversion, the pattern we observed is thus not inconsistent with previous findings and underlines that loss aversion is a fragile phenomenon that occurs only under rather specific circumstances. These findings may contribute to the ongoing debate on whether and under which circumstances loss aversion emerges (see also Walasek & Stewart, 2015; Yechiam, 2019; Yechiam & Hochman, 2013a, 2013b).

5 | CONCLUSION

The constructed nature of preferences makes them susceptible to features of the task context which, from a normative point of view, should be nonconsequential. Option complexity is such a feature. Our results indicate that even if option complexity plays a major role in the context of measuring risk attitude and age differences therein (Zilker et al., 2020), it seems to have little impact on other phenomena of preferential choice. Specifically, the framing effect and potential age differences therein were not found to be artifacts of differences in option complexity. Our

participants showed, on average, no loss aversion, and their preferences in the loss aversion task were not affected by differences in option complexity. That is, preferences in these tasks seem to be unaffected by option complexity—at least when materials are similar to those commonly used in the literature, for instance, in terms of difficulty. Option complexity seemed to contribute to younger but not older adults' delay discounting—an unexpected finding that may be further studied in future replication attempts and investigations of the underlying mechanisms.

AUTHOR CONTRIBUTIONS

V. Z. and T. P. conceptualized the study; V. Z. developed the experimental materials and programmed the experiment; V. Z. analyzed the data; V. Z. and T. P. interpreted the results; V. Z. wrote the original draft of the manuscript; V. Z. and T. P reviewed and edited the manuscript.

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How to cite this article: Zilker, V., & Pachur, T. (2021). Does option complexity contribute to the framing effect, loss aversion, and delay discounting in younger and older adults? *Journal of Behavioral Decision Making*, *34*(4), 488–503. https://doi.org/10.1002/bdm.2224