DISSERTATION

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Measuring and Modeling the Construction of Preferences in Decision Making under Risk

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Summary

When people are asked whether they like to take risks, their responses are typically consistent over time and predictive of real-world behavior. Hence, risk attitude can be regarded as a stable psychological trait (Frey et al., 2017). Yet, in behavioral risky choice tasks used in psychological and economic research—such as choices between lotteries, abstractly described in terms of outcomes and probabilities—behavior often varies considerably across measurement time-points and formats of the task (Frey et al., 2017; Pedroni et al., 2017). It seems paradoxical that decisions in these situations—which try to condense the problem of decision making under risk to its essential parts—are rarely an expressions of a person's stable, latent risk attitude. This dissertation examines why experimental risky choice behavior can be notoriously hard to predict, and how the methodological and theoretical apparatus with which we approach the study of risk preferences shapes the inferences we can make.

In the first chapter I introduce major theoretical perspectives on decision making under risk and the methods their proponents rely on. The notion of constructed preferences (Lichtenstein & Slovic, 2006; Slovic, 1995) is introduced as a general framework for understanding the lack of temporal stability and convergent validity of behavioral measures of risk attitude. According to this framework, behavioral risk preferences may be constructed on the spot, in the light of available cues and processing capacities. Hence, features of the choice environment—which have nothing to do with risk itself—and psychological characteristics of the decision maker—besides dispositional risk attitude—may profoundly shape the process and output of preference construction. In the subsequent chapters I investigate how surface features of stimulus materials, and individual differences in psychological characteristics, as well as their interplay, shape risky choice behavior. I also use different approaches of computational modeling to describe and explain these changes in risky choice and the underlying cognitive processes. In chapter 2 I demonstrate that in choices between a risky and a safe option, apparent age differences in risk attitude crucially depend on whether the options differ in complexity, rather than on age differences in latent risk attitude. In chapter 3 I investigate whether differences in option complexity also shape (age differences in) tasks used to measure framing effects, loss aversion, and delay discounting. This experiment identifies boundary conditions of the effects of option complexity. In chapter 4 I turn from focusing predominantly on behavior and its dependence on the anatomy of the task towards underlying cognitive processes. I demonstrate that risky choice behavior is shaped by differences between younger and older adults in the ability to implement selective attention. In chapter 5 I demonstrate why it may be useful to view risky choice through the lens of different formal theories—both economic and psychological ones—by identifying systematic signatures of attentional biases simulated in the attentional drift diffusion model in the parameters of cumulative prospect theory.

Overall, this dissertation shows why decision making under risk cannot be comprehensively understood in terms of latent risk attitude alone. It identifies specific contextual (option complexity) and psychological (selective attention) determinants of risky choice behavior which need to be taken into account as well, and explains how they affect the underlying process of

preference construction, using computational modeling. Moreover, this work underlines the merits of theoretical and methodological pluralism for studying the variable, context-sensitive aspects of risky choice behavior and individual differences therein.

Zusammenfassung

Wenn Personen gefragt werden, ob sie gerne Risiken eingehen, geben Sie typischerweise über die Zeit hinweg stabile Antworten, die auch echtes Verhalten vorhersagen. Daher kann Risikoeinstellung als ein stabiler psychologischer Charakterzug betrachtet werden (Frey et al., 2017). In Verhaltensaufgaben, die in der psychologischen und ökonomischen Forschung verwendet werden—zum Beispiel Entscheidungen zwischen Lotterien, die abstrakt in Form der möglichen Ergebnisse und ihrer Wahrscheinlichkeiten beschrieben werden—variiert Verhalten allerdings häufig über die Zeit und zwischen verschiedenen Formaten der Aufgabe (Frey et al., 2017; Pedroni et al., 2017). Es erscheint paradox, dass Entscheidungen in diesen Situationen—in denen das Problem des Entscheidens unter Risiko auf seine scheinbar essentiellen Aspekte reduziert wird—kaum Ausdruck der stabilen, latenten Risikoeinstellung der Person zu sein scheint. Diese Dissertation untersucht, warum in Experimenten gezeigtes Verhalten in Entscheidungen unter Risiko sehr schwer vorherzusagen sein kann und wie bestimmte wissenschaftliche Methoden und Theorien beeinflussen, welche Schlüsse wir über Risikopräferenzen ziehen können.

Das erste Kapitel stellt prominente Theorien und Messmethoden zum Entscheiden unter Risiko vor. Die Idee der Präferenzkonstruktion (Lichtenstein & Slovic, 2006; Slovic, 1995) dient als theoretischer Rahmen um die zeitliche Instabilität und geringe konvergente Validität von verhaltensbasierten, experimentellen Maßen der Risikoeinstellung zu verstehen. Es wird dabei angenommen, dass Verhalten in experimentellen Aufgaben im Moment der Entscheidungsfindung konstruiert wird und somit abhängig von der momentan verfügbaren Information und kognitiven Kapazitäten ist. Daher können Umgebungsmerkmale—welche nichts mit Risiko an sich zu tun haben—und psychologische Charakteristika—neben latenter Risikoattitüde—einen entscheidenden Einfluss darauf haben, wie Präferenzen konstruiert werden und welches Ergebnis dieser Konstruktionsprozess hervorbringt. In den folgenden Kapiteln wird untersucht, wie Oberflächenmerkmale von Stimulusmaterialien und psychologische Charakteristika, wie auch deren Interaktion, Entscheidungen unter Risiko beeinflussen. Verschiedene Ansätze der komputationalen Modellierung werden verwendet, um diese Veränderungen im Verhalten, sowie die zugrundeliegenden kognitiven Prozesse, zu beschreiben und zu erklären. In Kapitel 2 wird gezeigt, dass bei Wahlen zwischen einer sicheren und einer risikoreichen Option scheinbare Altersunterschiede in der Risikoeinstellung zwischen jüngeren und älteren Erwachsenen maßgeblich davon abhängen, ob sich die Optionen in ihrer Komplexität unterscheiden. In Kapitel 3 wird untersucht, ob Unterschiede in der Optionskomplexität auch Altersunterschiede in Aufgaben beeinflussen, die häufig verwendet werden, um Framing-Effekte, Verlustaversion, und die Abwertung zukünftiger Gewinne zu untersuchen. Dieses Experiment identifiziert Randbedingungen für die Effekte von Optionskomplexität. Kapitel 4 wendet sich den kognitiven Prozessen zu, die der Abhängigkeit des Verhaltens von der Struktur der Aufgabe zugrundeliegen. Es wird gezeigt, dass Risikoentscheidungen von Unterschieden in der Fähigkeit, selektive Aufmerksamkeit zu implementieren, abhängen. Kapitel 5 demonstriert, warum es nützlich sein kann, Risikoverhalten aus der Perspektive verschiedener psychologischer und ökonomischer Theorien zu betrachten. Dazu werden die Effekte von ungleicher Aufmerk-

samkeitsverteilung, simuliert im attentional Drift Diffusion Model, auf die Parameter von Cumulative Prospect Theory abgebildet.

Insgesamt zeigt diese Dissertation, dass Entscheidungen unter Risiko nicht hinreichend im Sinne von latenter Risikoeinstellung allein verstanden werden können. Sie identifiziert spezifische Kontextmerkmale (Optionskomplexität) und psychologische Merkmale (selektive Aufmerksamkeit), die ebenfalls beachtet werden müssen, und erklärt anhand von komputationaler Modellierung, wie diese Faktoren den zugrundeliegenden Prozess der Präferenzkonstruktion beeinflussen. Weiterhin unterstreicht die Arbeit den Nutzen von theoretischem und methodologischem Pluralismus für die Untersuchung der variablen, kontext-sensitiven Aspekte von Risikoentscheidungen, und von Unterschieden zwischen Individuen darin.

Contents

1 | General Introduction

1.1 What is Risk?

The most intriguing constructs in psychology are typically those that lack a commonly agreed-upon definition—concepts such as intelligence, rationality, and also risk. In daily use, risk often refers to the threat of dangers, losses or undesirable events in general (Aven, 2012). More broadly speaking, risk can be understood as a property of probabilistic environments with negative, neutral or positive outcomes. In behavioral research on decision making, risk is often defined by distinguishing it from certainty and uncertainty: In a world of *certainty*, each possible action invariably leads to a specific outcome, which is known to the decision maker (Luce & Raiffa, 1989). In decisions under *risk*, defined in the Knightian sense, each action leads to one of several possible outcomes, and the decision maker has full and precise knowledge about the outcomes and associated probabilities (Knight, 1921, see also Edwards, 1954). Throughout this dissertation I rely on this concept of risk. Finally, in decisions under *uncertainty* (Hacking, 2006; Knight, 1921; Luce & Raiffa, 1989), the probabilities and/or values of possible outcomes are not precisely known, due to reasons located within the decision maker (epistemic uncertainty), or they are even unknowable, due to an inherently stochastic structure of the world (aleatory uncertainty). In this dissertation, I mainly focus on decisions under risk, although certainty and uncertainty are encountered along the way.

Quantitatively, the risk of an option can, for instance, be measured as the variance of its possible outcomes, or as this variance normalized by the expected return—a dimensionless measure of risk (Weber et al., 2004).

Risk preference, in turn, refers to psychological responses to risk (Frey et al., 2017). Risk preferences have been studied in a rich literature spanning the disciplines of economics, psychology and cognitive science. Yet, different disciplines, and even schools of thought within disciplines, neither agree upon a common formal framework for modeling risk preferences, nor on a common experimental measure to elicit them—which is particularly troublesome given the low convergence between some of the existing measures (Frey et al., 2015; Pedroni et al., 2017).

In this dissertation I demonstrate how the theoretical and methodological apparatus with which we approach the study of risk preferences determines which kinds of inferences we (can) make—and why it can be so difficult to predict risky choice behavior reliably. I mainly focus on behavioral measures of risk preference, which show particularly weak convergence and test-retest reliability (Frey et al., 2017; Pedroni et al., 2017). My core thesis is that behavior in risky choice tasks often depends on features of stimulus materials besides risk itself, and on individual differences in psychological characteristics besides latent risk attitude. However, traditional theoretical frameworks make it easy to overlook such contextual and psychological variables, since they describe risk preferences by reference to (transformations of) outcomes and probabilities alone. This narrow focus can result in a failure to control or account for experimental confounds, thus generating a distorted and confusing picture of differences in risk preferences across tasks and groups of individuals.

I illustrate and address this problem by investigating how surface features of stimulus materials (the structural complexity of safe and risky options), and individual differences in psychological features (such as differences in attentional capacities due to cognitive aging) shape behavior in risky choice tasks. Moreover, I use different approaches in computational modeling to 1) describe the psychoeconomic structure of observed risky choice behavior, and to 2) explain its psychological underpinnings on the level of information processing. I also demonstrate how separate formal frameworks for modeling decision making under risk can be mapped onto each other, although they operate on different levels of explanation (Marr, 1982). This fosters a more integrative, holistic understanding of both empirical phenomena as well as formal frameworks for studying decision making under risk.

In this introduction, I embed the individual chapters conceptually, within prominent theoretical and methodological frameworks for studying risk preference, and give a brief outlook on each chapter.

1.2 From Normative to Descriptive Models: Neo-Bernoullian Theories

1.2.1 Expected Value and Expected Utility

In mathematics, the problem of decision making under risk has been normatively solved since 1654, when Blaise Pascal and Pierre Fermat formulated the concept of mathematical expectation in an exchange of letters (cf. David-Nightingale, 1962). Expectation maximization prescribes that decision makers should choose the option with the highest expected value (EV), defined as the sum across its n outcomes x, weighted by their objective probabilities p:

$$EV = \sum_{i=1}^{n} p_i \times x_i \tag{1.1}$$

Challenging the descriptive appropriateness of this principle, Nicolas Bernoulli (the cousin of Daniel Bernoulli) formulated the St. Petersburg paradox. He described a gamble where a coin is tossed until it comes up heads, and the player's reward doubles on each consecutive coin toss, starting from one ducat on the first toss. The paradox is that although this gamble in principle has an infinite EV, only few would be willing to pay infinite amounts of money for playing (Bernoulli, 1954). Daniel Bernoulli offered a solution to this paradox, by introducing the expected utility principle (1738/1954)[1]. Expected utility (EU) moves one step away from normative calculus towards subjective preferences, by replacing objective monetary values by the subjective utility the decision maker would derive from them:

$$EU = \sum_{i=1}^{n} p_i \times u(x_i) \tag{1.2}$$

The utility function $u(x_i)$ is assumed to be concave, capturing that the same increase in value becomes less significant when the value of goods already possessed increases. The concave utility function is reminiscent of the Weber-Fechner law in psychophysics, which describes a logarithmic relationship between stimulus magnitude and the intensity of sensations (Fechner, 1860), and it is still featured in several modern theories of decision making under risk (Birnbaum, 2005; Fishburn, 1970; Lopes, 1987; Tversky & Kahneman, 1992). The expected utility principle was

[1]The English translation of Bernoulli's work originally written in Latin in 1738 was published in 1954.

later axiomatized by von Neumann and Morgenstern (1945), and viewed as an appropriate theory of human reasoning and decision making for a while.

1.2.2 Behavioral Paradoxes

However, it soon became clear that empirical human behavior often contradicted EU. For instance, under EU, common consequences that are part of all options can be eliminated from consideration—but decision makers do not behave accordingly. For illustration, consider a choice between option A and B and a choice between option C and D:

option A offers	option B offers
a 100% chance to win \$1 Mio	a 89% chance to win \$1 Mio
	a 1% chance to win \$0
	a 10% chance to win \$5 Mio

option C offers	option D offers
a 89% chance to win \$0	a 10% chance to win \$5 Mio
an 11% chance to win \$1 Mio	a 90% chance to win \$0

Under EU the common 89% chance to win \$1 Mio in option A and B, and the common 89% chance to win \$0 in option C and D can be ignored. This elimination of common consequences makes A equivalent to C and B equivalent to D:

option A and C offer	option B and D offer
an 11% chance to win \$1 Mio	a 10% chance to win \$5 Mio
	a 1% chance to win \$0

Nevertheless, people typically prefer A over B while also preferring D over C. This preference pattern, known as the *Allais paradox* (Allais, 1953), can not be explained under any possible utility function in EU.

Kahneman and Tversky (1979) slightly modified the Allais paradox and showed that eliminating an equivalent 66% chance of winning \$2400 from a safe and a risky option had a greater impact on the desirability of the safe option than of the risky option. This phenomenon, known as the *certainty effect*, suggests a subjective overweighting of safe outcomes relative to merely probable ones (Kahneman & Tversky, 1979; Tversky & Kahneman, 1986)—thus violating the weighting by objective probabilities in EU. Further speaking against weighting by objective probabilities, people were found to exhibit the *fourfold pattern of risk attitudes*: People are risk averse for high-probability gains and low-probability losses, but risk seeking for low-probability gains and high-probability losses (Tversky & Fox, 1995; Tversky & Kahneman, 1992). The fourfold pattern comprises a reversal of preference patterns between the positive and negative domain (gains and losses) also known as the *reflection effect* (Kahneman & Tversky, 1979).

1.2.3 Prospect Theory and Cumulative Prospect Theory

These and other intriguing empirical demonstrations of EU's limits as a descriptive model of human risk preferences led to the development of prospect theory (PT; Kahneman & Tversky, 1979) and later cumulative prospect theory (CPT; Tversky & Kahneman, 1992). The authors set themselves the goal "to assemble the minimal set of modifications of expected utility theory that would provide a descriptive account of [...] choices between simple monetary gambles" (Kahneman

& Tversky, 2000, p.x)—and they did just that. In PT and CPT the carriers of subjective utility are no longer absolute end states, but changes in value compared to a reference point. CPT's value function $v(x_i)$ is concave for gains and convex for losses, capturing that changes in value are more difficult to discriminate the further they are away from the reference point. The value function is steeper for losses than for gains, capturing loss aversion—the observation that losses seem to have greater impact on preferences than gains of equal magnitude. Moreover, objective probabilities are replaced by decision weights π, derived from an inverse S-shaped probability-weighting function $w(p_i)$.[2] Hence, in CPT decision makers are assumed to choose the option with the highest valuation V:

$$V = \sum_{i=1}^{n} \pi_i \times v(x_i) \tag{1.3}$$

The nonlinear transformations of outcomes and probabilities in the value function and the probability-weighting function allow CPT to account for the Allais paradox, the certainty effect, the fourfold pattern, the reflection effect and several other benchmark violations of EU.

1.2.4 Modern Applications of CPT

Ever since, CPT has been one of the most influential modern economic theories of decision making under risk, culminating in Daniel Kahneman being awarded a Nobel Price in 2002[3]. Various fields still apply CPT to make sense of observed behavior, ranging form finance over insurance to psychology (Barberis, 2013; Camerer, 2000). Although Kahneman and Tversky (1979) largely refrained from ascribing specific psychological meaning to CPT's parameters, such psychological interpretations are intuitive and tempting, and modern psychology often takes the bait: Parameter estimates obtained by fitting CPT to empirical choice data are, for instance, used to assess subjective representations of probabilities and outcomes (Kellen et al., 2016), or to measure individual levels of optimism, pessimism, and probability sensitivity (Gonzalez & Wu, 1999). In chapter 2 of this dissertation I apply CPT, in combination with a stochastic choice rule, to disentangle systematic distortions of attributes from unsystematic errors (cf. Rieskamp, 2008), and to assess which of these components are affected by manipulating the complexity of options in risky choice tasks (more details below). In Chapter 5 I further identify a novel psychological interpretation for CPT's probability-weighting function, in terms of the relative amount of attention given to safe and risky options in risky choice.

1.2.5 The Persistent Rationale of Maximization

Note that EU, PT, and CPT moved away from rigid, normative principles *pre*scribing behavior of idealized agents, towards increasingly flexible functions *de*scribing behavior observed in humans. Critics disparagingly view the consecutive addition of free parameters as a "repair program" for Bernoullian logic (Berg & Gigerenzer, 2010, p. 135). It is true that this lineage of theories retained the core principle of maximization—picking the best option after multiplying and integrating (some function of) values and probabilities. In a non-judgmental manner, I will refer to such models as *neo-Bernoullian*.

[2]PT assumed decision weights on non-cumulative probabilities, and an initial editing phase, during which dominated options were eliminated. CPT assumed no editing phase and decision weights on cumulative probabilities instead, to preclude violations of stochastic dominance.

[3]Amos Tversky had died in 1996.

1.3 Psychological Concepts and Operationalizations of Risk Preferences

1.3.1 Lotteries as a Psychological Measurement Tool for Risk Preferences

Beyond the rationale of maximization, models within the neo-Bernoullian framework have another thing in common: Their assumptions are largely shaped by empirical insights obtained in choices between symbolically described lotteries, consisting of discrete outcomes $(x_1, ..., x_k, ..., x_n)$ with associated probabilities $(p_1, ..., , p_k = 1 - \sum_{i=1}^{k-1} p_i - \sum_{i=k+1}^{n} p_i, ..., p_n = 1 - \sum_{i=1}^{n-1} p_i)$, such as a choice between option A, offering a 100% chance to win \$50 and option B, offering a 50% chance to win \$100, and a 50% chance to win \$0. Such lotteries were not only essential in the development of economic theory, but are also frequently used as a psychological measurement tool for risk preferences (e.g., Pachur, Mata, et al., 2017; Rutledge et al., 2016). Risk preferences can be loosely defined as psychological responses to risk (Frey et al., 2017, more details below), and choices between lotteries promise to extract and isolate risk preferences in a highly structured and controlled manner: Much like thought experiments in philosophy (cf. Dennett, 2013), lottery choice tasks break down the rich problem of decision making under risk and amplify what is thought to be its essential parts—numerical properties of options. However, this sharp focus also creates blind spots. This becomes evident when considering that choices between described lotteries are only one tool in a vast and diverse set of psychological methods for studying risk preferences, which often produce divergent results.

1.3.2 Alternatives to Lotteries

Indeed, there are two major traditions for operationalizing risk preferences (Frey et al., 2017; Hertwig et al., 2019; Pedroni et al., 2017): Choices between lotteries belong to the *revealed-preference* tradition of measurement, which prompts and observes behavior in artificial choice situations involving risk. The structure of individual tasks within this tradition differs considerably, for instance in terms of the information presented, the response required, and the availability of feedback (Pedroni et al., 2017). In the *stated-preference* tradition of measurement, people are instead asked to self-report their introspective risk taking propensity, either in general (cf. Dohmen et al., 2011), or with respect to some specific scenario or domain (such as financial, recreational, or health-related risk taking, cf. Josef et al., 2016). Even more concretely, frequency measures ask how often a person engages in a particular risky activity, such as the number of cigarettes smoked per day (Heatherton et al., 1991). In terms of what they demand of the decision maker, individual measures within the stated-preference tradition resemble each other more closely than individual measures within the revealed-preference tradition.

1.3.3 Dispositional (Trait) or Constructed (State) Preferences?

This distinction between measurement traditions maps, to some degree, on a conceptual disagreement about the psychometric structure of risk preference (Frey et al., 2017; Hertwig et al., 2019; Mata et al., 2018): Is risk preference a stable, trait-like disposition, or does it vary substantially over time and situations, more like a state? The empirical preference reversals in choices about lotteries (which shaped EU, PT and CPT) seem to speak strongly in favor of context-dependence and variability. Indeed, behavioral measures of risk preference—where such preference reversals are frequently observed—only converge to a small degree, and display low test-retest reliability—suggesting a state-like structure (Frey et al., 2017). Interestingly though, stated-preference measures show substantial convergence and high test-retest reliability—indicating a stable, dispositional structure instead. Therefore, a general factor of risk preference, conforming to features of a stable psychological trait, can be identified—but this trait rarely becomes evident in (experimental) choice behavior (Frey et al., 2017). What is special about choice?

The notion of *constructed preferences* offers an explanation for this methodological and conceptual discrepancy (Lichtenstein & Slovic, 2006; Slovic, 1995; Warren et al., 2011): In choice tasks, participants may not implement stable, well-defined, and ordered preferences, but instead construct their preferences on the spot by actively processing whatever cues are available. The construction process may involve strategies such as discarding, overweighting, or cognitively restructuring certain information on the decision problem. Hence, diverse features of the choice context—which may have nothing to do with the options' risk itself—can shape the process and output of preference construction. Examples for context-variables that demonstrably shape choice behavior are response mode (Lichtenstein & Slovic, 1971; Lindman, 1971), time pressure (Maule & Svenson, 1993; Payne et al., 1993) and gain/loss framing (Kahneman & Tversky, 1984; Tversky & Kahneman, 1981). Hence, preference construction assigns a crucial role to the environment to explain the variability of risky choice behavior. Consistently, the greater diversity of information formats and demands of different behavioral measures of risk preference, compared to different stated-preference measures, maps onto a greater diversity of preferences observed, and conversely, a lower degree of convergence between behavioral methods.

Slovic's (1995) writing generates the impression that the idea of dispositional preferences might be entirely replaced by that of preference construction. However, there is no reason why observed inconsistencies in risky choice behavior should in principle preclude the existence of a dispositional risk attitude, especially given Frey et al.'s (2017) recent results. Rather, behavior may reflect the combined consequences of both disposition and construction (Simonson, 2008), and conditional on the specific measurement tool, one may override the other (Frey et al., 2017): While responses in propensity measures of risk attitude seem to be relatively well-explained in terms of dispositional risk attitude, responses in behavioral tasks can be understood within the general framework of constructed preferences. However, this conceptual framework alone does not allow to predict preferences in specific risky choice tasks reliably. To this end, the concrete factors shaping preference construction need to be comprehensively understood.

1.4 Determinants of Preference Construction

According to the notion of preference construction, two types of variables, besides risk and dispositional risk attitude itself, may systematically determine behavior in risky choice: Features of stimulus materials, that is, environmental variables, and features of the mind, that is, psychological variables.

1.4.1 Factors in the Choice Environment

As delineated previously, environmental characteristics (besides risk itself) are a staple for understanding constructed risk preferences. For instance, preferences reverse when the response format changes, that is, when people have to assign prices to lotteries instead of making binary choices (Binswanger, 1980; Lichtenstein & Slovic, 1971), or when probabilities are displayed in terms of fractions rather than decimals (E. J. Johnson et al., 1988). Moreover, different ways of communicating risk, either by numerically describing outcomes and probabilities (decision from description, DfD) or by granting first-hand experience through sampling the options' outcome distributions (decision from experience, DfE) entail choice behavior that either seems indicative of an overweighting or underweighting of rare events, respectively (Hertwig et al., 2004; Wulff et al., 2018). This phenomenon is known as the description-experience gap. Differences between description- and experience-based measures of risk preference have, among other things, been attributed to differential learning requirements of the tasks (Mata et al., 2011). Notably, higher learning requirements affect older adults more severely than younger adults, and thus distort inferences on age-differences in (dispositional) risk preference (Mata et al., 2011).

1.4.2 The Mind-Environment Fit

This insight is worth repeating: Varying task requirements do not affect preference in all individuals alike. Consequently, studying the environment alone is not sufficient to fully understand the behavioral variability of risk preferences—instead, individual differences in psychological characteristics (beyond dispositional risk attitude) have to be taken into account as well. Simon (1990, p.7) famously expressed this in the scissors metaphor: "Human rational behavior [...] is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor"—and one stands no chance of understanding the act of cutting by considering only one blade. Following this rationale, researchers have studied cognitive and other psychological variables that predict individual differences in risk preference, and how they interact with task characteristics.

1.4.3 Individual Differences in Psychological Characteristics

Maybe most prominently, behavior in risky choice tasks has often been linked to cognitive ability. To provide a concrete example, participants who perform better on the cognitive reflection test (CRT)—where each question invites an intuitive but incorrect response, which can be overcome by more reflective deliberation—tend to be less risk averse in choices about gains (Frederick, 2005). Likewise, a recent meta-analysis including diverse behavioral measures of risk preference found a weak but significant negative relationship between cognitive ability and risk aversion in the domain of gains (Lilleholt, 2019), and a similar pattern also emerges for self-reported risk preferences (Dohmen et al., 2018). Moreover, participants with lower numeracy (mathematical or quantitative literacy; Cokely et al., 2012) tend to make more inconsistent risky choices (Tymula et al., 2013).

To address how cognitive capacities interact with environmental features to shape preferences, comparisons between younger and older adults have proven particularly useful. Cognitive aging entails a well-established decline in fluid intelligence (Baltes, 1987; Craik & Bialystok, 2006; Horn & Cattell, 1967; Salthouse, 2004; Zaval et al., 2015), a component of general intelligence typically opposed to crystallized intelligence (Cattell, 1987). Fluid intelligence comprises the abilities to manipulate, comprehend and draw inferences based on novel information in real time (Craik & Bialystok, 2006; Zaval et al., 2015). Whether these age-related cognitive impairments affect decision making often depends on task demands: For instance, older adults tend to rely more on simpler strategies, which discard certain aspects of information (Mata et al., 2007), especially in choice problems with a high number of options (Besedeš et al., 2012a, 2012b). Moreover, a meta-analysis on pre-decisional information search concluded that older adults searched for less information before choice, especially if options were characterized by a greater number of attributes (Mata & Nunes, 2010). Similarly, in decision from experience, Frey et al. (2015) found that older adults sampled less per option than younger adults, but only under if the overall number of options was high. Moreover, older adults' adhere less to EV calculation (Mamerow et al., 2016; Pachur, Mata, et al., 2017), and this can induce the impression of age differences in risk preference when safe options systematically have higher EVs than risky options (Mamerow et al., 2016).

That is, since younger and older adults differ in cognitive abilities, they tend to respond differently to complex and cognitively demanding features of risky choice tasks. This can shape inferences on age differences in risk preference—and thus exemplifies the intricate interaction between mind and environment that constitutes constructed risk preferences.

In Chapter 2-4 of this dissertation, I demonstrate that previously overlooked differences in complexity between safe and risky options in lottery choice tasks affect cognitive processing and risky choice behavior differently in younger and older adults. In chapter 2, I experimentally manipulate the complexity of safe options to show that older adults are typically more likely to choose safe gains over risky gains—not because they are less risky, but because they are less complex. Chapter 3 tests the scope of this interaction between age group and option complexity, by extending the investigation to a wider range of choice tasks. In chapter 4, I investigate how differences in selective attention between younger and older adults shape risky choice behavior, and age differences therein, under varying levels of option complexity. These findings on the impact of environmental complexity and psychological capacities on the construction of risk preferences are formalized in terms of different theoretical frameworks. The next section outlines how this can, in principle, be achieved.

1.5 From Descriptive to Explanatory Models

To capture constructed preferences, formal theories need to account for the structure of the environment and for decision makers' psychological characteristics, such as limited knowledge and computational capacity—reminiscent of Simon's (1956, 1997) notion of *bounded rationality.* To which extent can different classes of models of decision making under risk capture these factors, and thus constructed preferences?

1.5.1 Neo-Bernoullian Constructed Preferences?

Let us first briefly return to neo-Bernoullian models. Since assumptions in these models were shaped by paradoxes and preference reversals, the framework might be well-adapted to study constructed, context-dependent and variable risk preferences. Indeed, CPT's value and probability-weighting function emulate a fundamental dependency of preferences on the numerical structure of the environment. Moreover, the proportion of individuals classified as best described by EU or CPT varies considerably across different behavioral tasks, thus capturing that decision makers do not seem to apply a task-general evaluation strategy (Pedroni et al., 2017). This illustrates that the neo-Bernoullian framework is well-suited to structurally describe risky choice patterns that vary across contexts and individuals in a compact manner, once these behaviors have been observed. However, since neo-Bernoullian models do not explicitly state how their parameters depend on specific environmental or psychological characteristics, they make it difficult to *predict* context-sensitive behaviors and individual differences therein reliably.

Moreover, neo-Bernoullian models are not models of the mind: To appreciate this, remember that neo-Bernoullian models transform objective outcomes and probabilities such that behavior viewed in reference to the transformed problem allows to maintain the assumption of maximization. This identifies an abstract representation of the problem that the decision maker seems to have solved—the functions that they seem to have computed—to produce observed behavior. Yet, even though decision makers behave *as if* they computed these functions, these models do not capture *how* they might have done this. In fact, it seems quite implausible that humans literally compute the psychoeconomic functions of CPT and similar models (Berg & Gigerenzer, 2010), and search processes in risky choice do not usually conform to those expected under a deliberate weighting and adding (Pachur et al., 2013; Su et al., 2013). Overall, the neo-Bernoullian formalism of maximization is simple for the modeler but difficult for the decision maker to implement (cf. Einhorn, 1971; Lindman & Lyons, 1978).

1.5.2 Formalizing the Process of Preference Formation

How else—if not by adding and weighting—might decision makers arrive at a choice, conditional on features of the task and of their own psychology? Under bounded rationality, the notion of maximizing—which is merely a function of selected features of the environment, and disregards the actor (Payne, 1973; Simon, 1990)—is replaced by *satisficing*, verbally a mixture between satisfying and sufficing. Satisficing decision makers do not look for an optimal outcome, but instead, for a satisfactory one, which meets an aspiration level, and is typically much easier to find (Simon, 1955). Under this perspective, the process of arriving at the decision, including information search and processing strategies, is as essential as the decision itself (Simon, 1997). Models that capture both of these aspects in a cognitively plausible way are commonly referred to as *process models* (cf. Lopes, 1995), and different families of process models can be distinguished.

Heuristics

One family of process models are heuristics—simple strategies which typically consist of a search rule, a stopping rule and a choice rule (Gigerenzer et al., 1999). For instance, the priority heuristic (PH, Brandstätter et al., 2006) assumes a lexicographic search process, where the minimum gain, the probability of the minimum gain, and the maximum gain of options in risky choice are considered sequentially (in that order), until one of these reasons is found to be decisive. Upon reaching an aspiration level, search is stopped and a choice is made. This processing strategy can predict the Allais paradox, the certainty effect, and several other benchmark violations of EU, which shaped the assumptions of CPT—and also offers an explanation for their cognitive roots. However, some authors have questioned the appropriateness of processing assumptions in PH (Glöckner & Betsch, 2008; Hilbig, 2008). This highlights a general intricacy of process modeling. Making processing assumptions explicit offers additional opportunity for disputing a model, since its predictions become more constrained. Conversely, data consistent with highly constrained (process-level) predictions can provide more impressive evidence in favor of a model, than if the predictions were less specific (Lewandowsky & Farrell, 2018; Roberts & Pashler, 2000).

Sampling-based Models

A second prominent class of process models are sampling-based models. Like heuristics, they are attractive since they do not require an explicit computation of psychoeconomic functions. Further speaking to their psychological plausibility, computation in the brain is likely to be implemented as a Bayesian sampler (Sanborn & Chater, 2016). For instance, the theory of Decision by Sampling (DbS, Stewart et al., 2006) assumes that decision makers perform a series of binary, ordinal comparisons between the options' outcomes and probabilities, and samples of these attributes drawn from memory. The rank of each attribute's value within the sample determines evaluations. These processing assumptions predict and explain the emergence of choice patterns indicative of concave utility functions, loss aversion, the overweighting of small probabilities and the underweighting of large probabilities—without requiring to literally compute CPT's functions.

Similarly, sequential sampling models (e.g., Link & Heath, 1975; Ratcliff, 1978; Ratcliff & Smith, 2004), which originate in signal detection theory (Swets, 1961; Tanner Jr. & Swets, 1954), formalize a deliberation process which is time-consuming but easy to implement: The decision maker continuously evaluates the possible consequences of choosing each option, until preference becomes strong enough to make a choice. For instance, random walk models (Bogacz et al., 2006) assume a continual sampling and comparison of noisy payoff distributions, constituting the options, until enough information is obtained to exceed a response threshold and make a choice. The response threshold conceptually closely resembles the aspiration level in satisficing (Simon, 1956). Decision field theory (DFT, Busemeyer & Townsend, 1993; Roe et al., 2001) explicitly applies these core principles of sequential sampling to risky choice, and successfully accounts for benchmark violations of EU, such as violations of strong stochastic transitivity and preference reversals between buying and selling the same item. Moreover, sequential sampling models generalize seamlessly from decision making under risk to uncertainty, since sampling does not require full knowledge of the distribution of outcomes and probabilities.

A whole class of sequential sampling models addresses the important role of attention in decision making (Busemeyer & Townsend, 1993; Krajbich et al., 2010; Krajbich & Rangel, 2011; Roe et al., 2001; S. M. Smith & Krajbich, 2019; Trueblood et al., 2014; Usher & McClelland, 2001, 2004). Maybe most prominently, the attentional Drift Diffusion Model (aDDM, Krajbich et al., 2010; Krajbich & Rangel, 2011) posits that looking longer at an option amplifies the impact of its value on evidence accumulation, and therefore on choice. This simple assumption allows the model to explain why people typically tend to choose the option that they look at longer (Armel et al., 2008; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Glöckner et al., 2012; Glöckner & Herbold, 2011; Konovalov & Krajbich, 2016; Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011; Shimojo et al., 2003; Stewart et al., 2016), in risky choice and other domains (S. M. Smith & Krajbich, 2018). The processing perspective can thus pinpoint specific cognitive variables that contribute to risk preferences—such as attentional biases—which neo-Bernoullian theories are blind to. The narrow focus on outcomes and probabilities in models like CPT makes it difficult to even begin thinking about attention as a potentially determinant of risky choice, and almost impossible to express specific hypotheses in this regard.

In chapter 4 I use the attentional drift diffusion framework to investigate differences in information processing under selective attention between younger and older adults, and their impact on age differences in risky choice. In chapter 5 I demonstrate how the process-model perspective can help identify psychological underpinnings of psychoeconomic functions in neo-Bernoullian models.

1.5.3 Matching Models and Experimental Methods

As previously established, choices between described lotteries directly reflect the neo-Bernoullian rationale that outcomes and probabilities capture the essence of decision making under risk. The process-based framework highlights that this approach falls short of capturing how people search, manipulate and integrate outcome and probability information—which is crucial for fully understanding risk preferences from a constructed-preference perspective. Consequently, the process-oriented tradition comes with its own distinct set of experimental tools, namely process-tracing methods that directly capture information acquisition (Schulte-Mecklenbeck et al., 2011). For instance, information boards (Payne, 1976) and MouseLab (Bettman et al., 1990; E. J. Johnson et al., 1989; Payne et al., 1993) capture how participants sequentially open physical envelopes or fields on a computer screen containing outcome or probability information. Mouse-tracking (Franco-Watkins & Johnson, 2011; Koop & Johnson, 2011) and eye-tracking (Orquin & Loose, 2013; Rayner, 1998; Stewart et al., 2016) capture continuous movements of mouse-cursors and eyes during information search and response selection. Thereby obtained processing signatures can either be analysed in their own right or incorporated into computational models. By formally modeling response time data, different aspects of processing can also be dissociated parametrically, without directly monitoring search (Ratcliff, 1978; Ratcliff & Smith, 2004). Although less immediate, this approach can be applied to simpler data.

1.6 Connecting Different Levels of Explanation

We have considered two influential formal frameworks for studying decision making under risk, the neo-Bernoullian and process-related framework. Although they differ considerably in their conceptual and methodological implications, the two frameworks are not necessarily strictly competing accounts. Note, for instance, that many choice patterns can be correctly predicted by both CPT and PH (Brandstätter et al., 2006). Moreover, the processing assumptions in DbS give rise to CPT's psychoeconomic functions (Stewart et al., 2006), without literally computing them, and some random walks which can implement EV maximization (Bogacz et al., 2006) without applying the algebraic calculus of adding and weighting. These observations highlight that neo-Bernoullian and process models may be compatible rather than competing accounts of the same behavioral phenomena—which operate on different levels of explanation (cf. Marr, 1982). For instance, CPT's iconic psychoeconomic functions can be viewed as an abstract description of behavior that emerges, when realistic agents implement simple processing strategies, like heuristics or sampling-based strategies (cf. Pachur, Suter, et al., 2017, and chapter 5 of this dissertation). That is, while neo-Bernoullian models describe construct*ed* preferences, meaning behavioral outputs of the construction process, process models capture the active process of construction itself. In this sense, both have their place in the theoretical landscape of decision making under risk, rather than competing for the same niche. In the end, what one considers a (more) satisfying explanation may depend on subjective phenomenological markers (Gopnik, 1998). I employ both frameworks, and their associated experimental methods, throughout this dissertation, thus demonstrating how they can complement each other. Chapter 5 explicitly addresses the potential for theory integration between neo-Bernoullian and process models, by showing that the attentional drift diffusion framework can be used to identify attentional underpinnings for characteristic shapes of CPT's probability-weighting function.

1.7 Overview of the Dissertation

In this dissertation I investigate how the conceptual and methodological apparatus with which we approach the study of decision making under risk determines which kinds of inferences we (can) make—and why it can be so difficult to predict risky choice behavior accurately. Each chapter of this dissertation has been prepared for publication, and can thus also be read as self-contained.

In chapter 2, I demonstrate experimentally how differences in option complexity between safe and risky options, a longtime overlooked confound in lottery choice tasks for the behavioral measurement of risk attitude, distort inferences on age differences in risk attitude. In two experiments, I show that older adults are more likely to choose safe gains and to reject safe losses than younger adults—but only if these safe options are simpler than their risky alternatives. Experimentally increasing the complexity of safe options eliminated such age differences. These preference shifts are not explained by complexity aversion, or by an increase in non-systematic errors. Rather, modeling in CPT suggests that the availability of simple safe options amplifies systematic distortions in the probability-weighting function and the value function.

In chapter 3, I investigate whether differences in option complexity also distort the measurement of age differences in other prominent phenomena in risky and risk-free choice, namely loss aversion, framing effects, and delay discounting. Contrary to our hypotheses, manipulating differences in option complexity in these tasks barely affected choice behavior, and age differences therein. I discuss which features of these tasks may serve as boundary conditions for the impact of option complexity on constructed preferences.

Chapter 4 moves further along the spectrum from descriptive towards explanatory approaches and directly targets age differences in cognitive processing of risky choice materials. Using eye-tracking and modeling in the attentional drift diffusion framework, I demonstrate that risky choice behavior is shaped by differences in attentional capacities between younger and older adults, especially in choices between safe and risky options that differ in complexity. By applying methods and theories which originate outside of the world of risky choice, I thus obtain a process-based explanation for why traditional risky choice tasks make it so difficult to reliably capture risk preferences and age differences therein.

Chapter 5 demonstrates on a more abstract level why it may be useful to view risky choice through the lenses of diverse economic and psychological theories—even theories that superficially seem to have little to do with each other. In a cross-theory parameter recovery between the attentional drift diffusion model and CPT I show that seemingly disparate constructs in both theories, attentional biases and probability weighting, may accommodate the same behaviors. Thereby I identify innovative process-based explanations for iconic probability-weighting functions prevalent in the risky choice literature—and for the associated empirical findings, such as the certainty effect and the description-experience gap.

Chapter 6 synthesizes the results from chapters 2-5 and carves out the main empirical and theoretical contributions, and embeds them in the broader discussions they contribute to.

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2 Age Differences in Risk Attitude are Shaped by Option Complexity

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Chapter 2 is hence not identical to the final published article! At the time this dissertation was submitted at the FU Berlin the article had not yet been published.

Abstract

The canonical conclusion from research on age differences in risky choice is that older adults are more risk averse than younger adults, at least in choices between options with possible gains. However, most of the evidence for this conclusion derives from studies that have investigated a specific type of choice problem: choices between a safe and a risky option. However, safe and risky options differ not only in the degree of risk but also in the amount of information to be processed—that is, in their complexity. We demonstrate that differences in option complexity are a key driver of age differences in risk attitude: When the complexity of the safe option is increased, older adults no longer seem more risk averse than younger adults (in gains). Using computational modeling, we compare candidate mechanisms underlying the effect of option complexity on risky choice: Results show that participants are not simply averse to complexity, and that increasing safe options' complexity does not only make responses more noisy. Rather, differences in option complexity affect the impact of attribute information on preferences: the availability of a simple safe option is associated with the distortion of probability weighting and decreased outcome sensitivity. When both options' complexity becomes more similar, these effects are attenuated. We also dissociate the effect of option complexity from an effect of certainty on risky choice. We conclude by discussing possible implications of our results for other phenomena in decision making (e.g., framing effects, loss aversion, immediacy effects).

2.1 Introduction

In many—perhaps most—of life's decisions, people cannot be certain about which of the potential outcomes will actually materialize. At best, they have some information about the probability that the outcomes will occur, making them *decisions under risk* (Knight, 1921). A key behavioral regularity in decisions under risk is that people seem to be *risk averse*, that is, to find riskier options (defined as those having a larger variance in the possible outcomes; Markowitz, 1952) less attractive than less risky ones. To illustrate, when asked to choose between a risky option offering a 80% chance to win $4,000 (otherwise nothing) and a safe option of $3,000 for sure, most people prefer the latter, although the former option's expected value is higher (e.g., Kahneman & Tversky, 1979).[1] People's risk attitude, that is, the degree to which they are risk averse or risk seeking, has been shown to be sensitive to a number of factors, such as the domain (e.g., people tend to be risk seeking when evaluating options with possible losses; Kahneman & Tversky, 1979) and the magnitude of the outcome offered (people are more risk averse when the outcomes are very high, Holt & Laury, 2002). In addition, there are considerable individual differences in risk attitude, which have been associated with, for instance, personality (e.g., Becker et al., 2012) or cognitive ability (Dohmen et al., 2018; Henninger et al., 2010). Moreover, there are robust gender differences, with females often showing higher risk aversion than males (e.g., Charness & Gneezy, 2012).

Which of an individual's characteristics affect their risky choices? One characteristic that has attracted much attention is age—in particular, how does risky choice differ in older adults, relative to younger ones? A common conclusion is that older adults are more risk averse than younger adults in the domain of gains (Best & Charness, 2015; Mather et al., 2012; Rutledge et al., 2016; Tymula et al., 2013). In this article, we highlight that much of the evidence for greater risk aversion in older age stems from one type of choice problem—namely choice between a safe and a risky option. For instance, when asked to choose between a risky option offering a 20% chance to win $50 (otherwise nothing) and a safe gain of $10, older adults are more likely than younger adults to prefer the safe option (e.g., Mather et al., 2012). Choice problems consisting of a safe and a risky option have several practical advantages. For instance, they allow researchers to easily vary the difference in risk between the options by keeping the safe option constant while increasing or decreasing the variance of the risky option, thus capturing fine-grained degrees of risk aversion. Safe and risky options, however, differ not only in their degree of risk; they also differ in the amount of information to be processed—that is, in their complexity. Unlike safe options, risky options consist of multiple pieces of information that together make up its anatomy. For illustration, even the simplest risky option consists of two outcomes and their respective probabilities, whereas a safe option is fully described by a single number (the only outcome).

We provide evidence that this difference in structural *option complexity*—defined presently as the number of elements that characterize an option—is a key driver of differences between younger and older adults typically observed in risky choice.[2] We demonstrate that once complexity differences between options are attenuated, the age differences in the risk attitude disappear. This difference in option complexity between risky and safe options might help to explain puzzling inconsistencies in the literature on age differences in decision making under risk. Last but not

[1] The expected value (EV) of a risky lottery is defined as the sum of all possible outcomes weighted by their probabilities. The tendency to choose the option with the higher EV is commonly used as a standard to judge decision quality.

[2] Clearly, complexity includes other dimensions as well. We focus on the number of elements here because it is the most relevant one for conceptualizing differences between risky and safe options in the common risky choice paradigm.

least, we investigate the cognitive mechanisms underlying the effect of option complexity on risky choice.

In what follows, we first review the evidence regarding age differences in risk attitude and describe the potential role of option complexity in their emergence. We then derive hypotheses about cognitive mechanisms possibly underlying the effects of complexity in risky choice in older and younger adults. Finally, we report an online (Study 1) and a lab study (Study 2) that test these hypotheses by analyzing behavioral patterns and by employing computational modeling based on cumulative prospect theory (CPT; Tversky & Kahneman, 1992).

2.1.1 Age Differences in Risky Choice: An Overlooked Task Dependency

A standard behavioral approach to examine age differences in risk preferences is to have people make choices between options with differing levels of risk. In most studies with this approach, older adults appear to be more risk averse than younger adults, at least in the domain of gains (e.g., Mather et al., 2012; Rutledge et al., 2016; Tymula et al., 2013). In their meta-analysis summarizing 18 studies using behavioral tasks to examine age differences in risky choice, Best and Charness, 2015 concluded that, overall, older adults were more risk averse than younger adults in the gain domain ($-0.25, 95\%$ CI $[0.33, 0.18]$), whereas there were no robust age differences in the loss domain ($-0.02, 95\%$ CI $[-0.10, 0.06]$). Yet findings from some individual studies in the domain of gains violate this pattern. For instance, Mather et al., 2012 did not find general age differences in the tendency to choose the more risky gain (we discuss these results in more detail below), and in Pachur, Mata, et al., 2017 and Kellen et al., 2017 older adults made even more *risk seeking* choices in the domain of gains than younger adults. Table 2.1 provides an overview of existing findings (focusing on studies with described probability and outcome information; for an overview of studies in which this information has to be learned from experience, see Mata et al., 2011).

How might these seemingly inconsistent results be reconciled? A closer look at the stimuli used in the different studies reveals a striking yet hitherto largely neglected difference. Almost all studies observing higher risk aversion in older than in younger adults (in the domain of gains) examined choices between a safe and a risky option; in contrast, studies reporting no age differences or the opposite pattern examined primarily choices between two (more or less) risky options: In Pachur, Mata, et al.'s (2017) and Kellen et al.'s (2017) studies—both of which found that older adults were more likely to choose the more risky gain—most choice problems consisted of two risky options, such as a choice between option A, offering \$23 with a chance of 44% or \$31 with a chance of 56%, and option B, offering \$62 with a chance of 74% or \$0 with a chance of 26%. Likewise, Henninger et al., 2010, who also found higher risk seeking in older adults' choices, employed the Cambridge Gambling Task, in which all gain options involve risk.

Table 2.1: Results from Previous Studies on Age Differences in Risky Choice, By Type of Choice Task

Type of Task Used	*n* Subjects[a]	Range	Age *M*	*SD*	Results by Domain Gains	Losses	Mixed[b]
Safe vs. Risky (Lotteries)							
Rutledge et al., 2016	25189	18–69			OA more risk averse	No age difference	OA more risk seeking
Tymula et al., 2016	135	12–90			OA more risk averse than YA and MA	OA more risk seeking than AD, YA, and MA	–
	- AD	12–17					
	- YA	21–25					
	- MA	30–50					
	- OA	65–90					
Mather et al., 2012							
Experiment 1	38 YA		18.7	(1.1)	OA more risk averse than YA	–	–
	38 OA		67.5	(5.4)			
Experiment 2	48 YA		20.8	(3.5)	OA more risk averse than YA	–	–
	48 OA		72.4	(6.7)			
Experiment 3	20 YA		21.1	(2.0)	–	OA more risk seeking than YA	–
	20 OA		68.8	(6.8)			
Experiment 4	107 YA		29.46	(7.17)	–	–	OA avoid safe losses more than YA
	50 OA		59.30	(4.04)			
Weller et al., 2011	358 EA	18–22			OA and MA more risk averse than EA and YA	No age difference	–
	106 YA	24–44					
	61 MA	44–64					
	61 OA	65–85					
Mamerow et al., 2016	902	18–90	47.4	(17.4)	No age difference	–	–
Lauriola et al., 2001	26 YA	21–40			OA more risk averse than YA; EA more risk averse than OA	OA more risk seeking than YA and EA	
	27 OA	41–60					
	23 EA	61–80					
Lee et al., 2007	21 YA		29.9	(6.2)	–	–	OA more risk averse than YA
	9 OA		65.2	(4.2)			
Safe vs. Risky (Framing)							
Mayhorn et al., 2002	58 YA		29.9	(3.2)	No age difference[c]	No age difference	No age difference
	58 OA		70.3	(4.8)			
Mikels and Reed, 2009	22 YA		19.77	(1.19)	No age difference	YA more risk seeking	–
	22 OA		71.55	(4.48)			
Kim et al., 2005	186 YA	17–28			OA more susceptible to framing effect[d]		
	186 OA	58–78					
Bruine de Bruin et al., 2007	360	18–88	47.7	(17.0)	OA more susceptible to framing effect		
Rönnlund et al., 2005	192 YA		69.1	(3.5)	YA and OA equally susceptible to framing effect		
	192 OA		23.8	(7.4)			
Watanabe et al., 2010	661 YA	20–64	44.8		YA more susceptible to framing effect		
	168 OA	65–92	72.5				
Thomas and Millar, 2011							
Experiment 1	120 YA		19.4		No age difference	OA more/equally risk seeking than YA[e]	–
	120 OA		74.3				
Experiment 2	136 YA		20.1		No age difference	No age difference	–
	136 OA		20.1				
Risky vs. Risky (Lotteries)							
Mather et al., 2012							
Experiment 1	38 YA		18.7	(1.1)	No age difference	–	–
	38 OA		67.5	(5.4)			
Experiment 2	48 YA		20.8	(3.5)	No age difference	–	–
	48 OA		72.4	(6.7)			
Experiment 4	107 YA		29.46	(7.17)	–	–	No age difference
	50 OA		59.30	(4.04)			
Pachur et al., 2017	60 YA	18–30	23.6	(3.1)	OA more risk seeking	OA more risk averse	OA more risk averse
	62 OA	63–88	71.3	(6.4)			
Kellen et al., 2017	30 YA	18–34			OA more risk seeking	OA more risk seeking	OA more risk seeking[f]
	30 OA	61–78					
Risky vs. Risky (Cambridge Gambling Task)							
Henninger et al., 2010	58 YA		23.4	(4.4)	OA more risk seeking	–	–
	54 OA		70.7	(3.0)			
Deakin et al., 2004	177	17–79	41.0	(15.1)	–	–	OA more risk averse
Zamarian et al., 2008	33 YA	18–54	36.1	(13.7)	–	–	No age difference
	52 OA	55–88	69.3	(7.0)			
Risky vs. Risky (Blackjack)							
Dror et al., 1998							
Experiment 1	42 YA	18–33	20.9	3.2			No age difference
	45 OA	61–85	70.5	(5.5)			
Experiment 2	50 YA	18–39	21.0	(4.4)			No age difference
	53 OA	62–86	71.0	(5.2)			

[a] AD = adolescents, YA = younger adults, MA = middle-aged adults, OA = older adults, EA = elderly adults.
[b] Mixed problems involve options with both positive and negative outcomes, such as a 50% chance to win 20$ and a 50% chance to lose 15$.
[c] Except in one scenario.
[d] Greater framing effect indicates a greater difference in risky choice behavior between gains and losses, typically higher risk aversion for gains and/or higher risk seeking for losses.
[e] Depending on type of secondary task.
[f] Except in choices between mixed lotteries and loss-only lotteries.

Mather et al., 2012 used both choice problems involving a risky and a safe option and two risky options. Age differences in risky choice behavior emerged only if a safe option was available, with older adults showing greater risk aversion in the domain of gains and greater risk seeking in the domain of losses than younger adults. In problems with two risky options, by contrast, there were no age differences. Mather et al., 2012 attributed this finding to a stronger certainty effect in older adults. The certainty effect describes a relative overweighting of certainty: For instance, the difference between 100% and 85% is weighted more heavily than the difference between 90% and 75% (despite being nominally of the same magnitude). One of the most prominent explanations for the certainty effect is provided by CPT (Tversky & Kahneman, 1992), a model that describes regularities in risky choice in terms of non-linear transformations of outcome and probability information. In CPT (Tversky & Kahneman, 1992), the certainty effect is captured by an inverse S-shaped probability weighting function that transforms objective probabilities into subjective decision weights (for details and a formal definition see the section "Testing the underlying mechanisms: Computational modeling"). The inverse S-shape of the weighting function has been attributed to affective responses: situations triggering fear or hope (i.e., whenever the probability of winning is less than 1) and situations devoid of those emotions (whenever the probability of winning is equal to 1) are treated as categorically different (Lopes, 1987; Rottenstreich & Hsee, 2001), leading to large jumps in probability weighting at the extreme ends of the probability scale.

2.1.2 Task-Dependent Age Differences in Risky Choice: The Potential Role of Option Complexity

Here we offer a different, and, in principle, complementary, explanation of why age differences in risky choice or lack thereof critically depend on the presence or absence of a safe option. In contrast to the certainty-effect account, our explanation attributes the differences to cognitive rather than affective factors. It builds on the finding that risk aversion in choices between safe and risky gains is negatively associated with cognitive ability (Dohmen et al., 2018) and the well-documented age-related decline in fluid cognitive ability (Baltes, 1987; Craik & Bialystok, 2006; Horn & Cattell, 1967; Salthouse, 2004). Specifically, we argue that the presence of safe options may influence the emergence (and possibly the direction) of age differences in risk attitude not (only) because their outcomes are certain, but because they are less complex than risky options: In choice problems involving a safe and a risky option—in which age differences in risky choice behavior are typically observed—the options differ substantially in complexity. In contrast, in choice problems with two risky options—in which age differences in choice are attenuated, eliminated, or even reversed—differences in complexity between options are much smaller. We suggest that the age differences typically observed in choices involving safe options are not primarily due to genuine differences in risk attitude, or to older adults responding more strongly to certainty than younger adults but stem from older adults' response to option complexity. This seems consistent with age-related declines in fluid intelligence (Craik & Bialystok, 2006; Horn & Cattell, 1967; Zaval et al., 2015), which in turn have been drawn upon to explain age differences in several dimensions of decision making (e.g. choice, information search). Those age differences appear to occur especially in complex and demanding tasks (cf. Frey et al., 2015; Mamerow et al., 2016; Mata et al., 2007; Zaval et al., 2015). On a neurobiological level, these impairments in information processing have been linked to changes in dopaminergic neuromodulation, affecting, for instance, the signal-to-noise ratio of neural processing (Li et al., 2001). Moreover, aging is associated with structural and functional impairments in the (dorsolateral) prefrontal cortex (Rypma et al., 2001; Salat et al., 2005; West, 1996), which in turn is implicated in decision-relevant working memory functions such as manipulating and integrating different pieces of information (Curtis & D'Esposito, 2003; D'Esposito et al., 1995; Krawczyk, 2002; Rypma & D'Esposito, 2000).

Our complexity account and Mather et al.'s (2012) certainty account make different predictions about how age differences in risky choice behavior should differ between problem types. Notably, the choice problems used in Mather et al., 2012 do not allow for the possible effects of certainty versus complexity to be disentangled as the safe options were always less complex than the risky ones. Turning to similarly complex safe and risky options, however, would permit the certainty-effect and the complexity accounts to be dissociated. To construct such a problem type, we increased the complexity of safe options by expressing the safe outcome as a mathematical term rather than a single number, thus rendering its complexity more similar to the complexity of the risky option (see Figure 2.1 for an example, and the section "Materials" for more detail). Comparing choices in this problem type to choices between a simple safe and a complex risky option isolates the effect of complexity. Furthermore, comparing this problem type to choices between two complex risky options isolates the effect of certainty. The most basic prediction of the complexity account is that age differences in the tendency to choose the safe option should emerge if the options differ in complexity (involving a simple safe option) but that they should be reduced (or eliminated) with smaller or no differences in option complexity (involving a complex safe option). By contrast, the certainty account does not predict a change in age differences between these two problem types, as both involve a safe option. It does predict, however, reduced age differences in the tendency to choose the less risky option in a condition with two risky options, compared to a condition with complex safe options—which differ in certainty, but not complexity. Let us emphasize that, although they make distinct predictions, the two accounts are not mutually exclusive: Older adults may be more sensitive to both certainty and complexity than younger adults are.

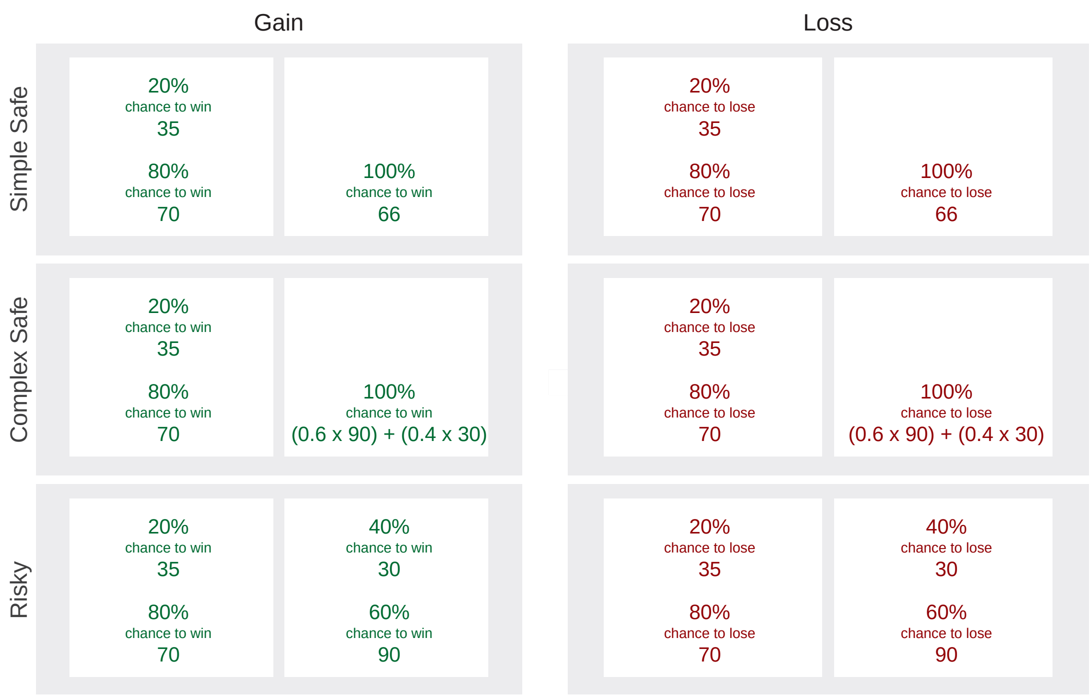

Figure 2.1: Conditions of the risky choice task: Exemplary choice problems by problem type and domain.

2.1.3 How Might Complexity Affect Age Differences in Risky Choice?

In addition to examining whether complexity affects the emergence of differences between younger and older adults in risky choice, we were also concerned with *how* complexity might exert its influence on choice behavior. We next describe four candidate mechanisms. Each mechanism entails specific testable predictions, all of which are summarized in Table 2.2 and elaborated below.

Complexity aversion hypothesis

One possible mechanism by which option complexity impacts choice behavior is that people find more complex options generally less attractive—due to their greater computational effort required for their evaluation (e.g., due to their lower processing fluency; less fluent stimuli are often perceived as less attractive than fluent ones (Alter & Oppenheimer, 2009). Consistent with complexity aversion, Bernheim and Sprenger, 2019 argued that people prefer lotteries with fewer outcomes that are easier to understand, and that the certainty effect may be a special case of this more general phenomenon. Moreover, both Huck and Weizsäcker, 1999 and Sonsino et al., 2002 found that participants choosing between lotteries that differed in the number of available outcomes preferred the lottery with fewer outcomes (which were thus less complex). Similarly, in Mador et al., 2000, participants assigned lower prices to more complex lotteries (in terms of the number of outcomes) than to simpler lotteries, even when the simpler lottery had a lower expected value than, or was stochastically dominated by, the more complex lottery. Kovářık et al., 2016 had their participants rank, in order of preference, lotteries that were described as more or less complex sequences of probabilistic events. For instance, a multi-stage lottery could consist of a coin toss that determined the composition of an urn, with the color of a chip drawn from that urn determining the final outcome. Most participants ranked the simpler but otherwise identical versions higher than the more complex versions. Due to their declining fluid cognitive abilities (also defined as the ability to analyse complex relations and to draw inferences, cf. Cattell, 1963; Craik & Bialystok, 2006; Horn & Cattell, 1967), older adults might show a stronger aversion to complexity than younger adults. The complexity-aversion hypothesis thus predicts that older adults are more averse to more complex options than younger adults are. As a consequence, increasing an option's complexity should decrease older adults' likelihood of choosing that option more than it decreases younger adults', in both gain and loss domains alike.

Response-noise hypothesis

A second possibility is that rather than directly affecting the subjective utility of the options, complexity increases the error in mapping the valuation of the options onto a response. Response noise is often formalized in the context of a probabilistic choice rule, using a parameter that governs the probability that an option, viewed as more attractive, is actually chosen (e.g., Olschewski et al., 2018; Rieskamp, 2008). In choices between risky lotteries, response noise has been found to be higher under greater cognitive load (Olschewski et al., 2018). To the extent that higher complexity induces cognitive load, it might also increase response noise. Overall, this should shift the proportion of choices of the safe option toward 50%, that is, risk neutrality. Given that people are typically risk averse in the domain of gains and risk seeking in the domain of losses (Kahneman & Tversky, 1979), higher response noise should thus lead to a reduction in risk aversion in the gain domain, and an increase in risk aversion in the loss domain. Since older adults display higher response noise and make more inconsistent choices than younger and middle-aged adults (Pachur, Mata, et al., 2017; Tymula et al., 2013), the response-noise hypothesis predicts that the increase in response noise under higher complexity will be more pronounced in older than in younger adults. If this is the case, the common age differences in choices between simple safe and complex risky option risky options—that is, older adults making more risk-averse (/risk-seeking) choices than younger adults in choices about gains (/losses)—should be reduced when both options are similarly or equally complex.

Table 2.2: Possible Mechanisms Underlying an Effect of Option Complexity on Risky Choice: Each Mechanism Makes Specific Predictions about the Effect of Increasing Safe Options' Complexity on One or Several Outcome Variables

Mechanism Outcome variable	Prediction
Complexity-aversion hypothesis	
Risky choice behavior	Increased risk seeking in both gain and loss domain
Response-noise hypothesis	
ρ parameter	Decrease in ρ (more noise)
Risky choice behavior	Higher risk neutrality (choice proportion closer to 50%)
Probability-weighting hypothesis	
γ parameter	Increase in γ (more linear probability weighting)
Risky choice behavior	Increased risk seeking in gain domain Increased risk aversion in loss domain
Outcome-sensitivity hypothesis	
α parameter	Increase in α (higher outcome sensitivity)
Risky choice behavior	Increased risk seeking in gain domain Increased risk aversion in loss domain

Probability-weighting hypothesis

A third possibility is that option complexity might affect the processing of specific attribute information. That is, rather than generally decreasing an option's attractiveness (as assumed by the complexity-aversion hypothesis) or making the mapping of the valuation onto the response more error-prone (as assumed by the response-noise hypothesis), higher complexity might affect how people extract and integrate attribute information on the options. According to the probability-weighting hypothesis, complexity differences affect probability weighting, a key construct in CPT, which describes how objective probabilities are transformed into subjective decision weights (a formal description is provided in the section "Testing the underlying mechanisms: Computational modeling"). This hypothesis is based on the observation by Glöckner et al., 2016 (in a study on younger adults; we refer to the data in the description condition) that choices between a safe and a risky option—that is, choices differing in complexity—give rise to a more curved probability weighting function than choices between two risky options that do not differ in complexity.

Moreover, the findings by Mather et al., 2012 suggest that this effect may be more pronounced in older than in younger adults. To recap, Mather et al. found no age differences in choices between two risky options, but that older adults had a higher (lower) tendency to choose the safe gains (losses) in choices between a safe and a risky option. The strongly curved weighting function, observed in choices between a safe and a risky option in younger adults cf. Glöckner et al., 2016, may therefore be even more strongly curved in older adults. In contrast, in choices between two risky options younger and older adults may both show a moderately curved weighting function. This would imply that probability weighting is more sensitive to the availability of safe options in older than in younger adults.

Our complexity account thus predicts more linear probability weighting in a condition with *complex safe* options than in a condition with *simple safe* options, especially in older adults. The certainty-effect account does not predict these differences in probability weighting; rather, it predicts that, due to differences in certainty, probability weighting will differ between choices with *complex safe and risky* options and choices with *two risky* options.

Outcome-sensitivity hypothesis

Complexity might also affect the processing of outcome information, that is, how objective outcomes are subjectively represented. In CPT, objective outcomes are transformed into subjective values according to a value function, which exponentiates the outcome magnitude by an outcome sensitivity parameter (a formal description is provided in the section "Testing the underlying mechanisms: Computational modeling"). For values of the outcome sensitivity parameter smaller than 1 (i.e., concave value functions), differences between the outcomes' magnitudes are attenuated; for values of the outcome sensitivity parameter larger than 1 (i.e., convex value functions), differences are amplified. Notably, in choices between safe and risky options, the largest outcome in the choice set is typically offered by the risky option (unless the safe option dominates the risky option) such that the value function tends to amplify or attenuates the subjective value of the risky option more than that of the safe option. As a consequence, a more concave value function entails greater risk aversion in the domain of gains and greater risk seeking in the domain of losses.

Based on these insights, we can now use Mather et al.'s (2012) results to derive predictions about the possible effects of option complexity on outcome sensitivity. If older adults are more risk seeking for gains and more risk averse for losses in choices between two risky options than in choices between a simple safe and a risky option, this could indicate a steeper value function. Hence, the outcome-sensitivity hypothesis predicts an increase in outcome sensitivity in problems with complex safe and risky options relative to problems with a simple safe and a risky option, especially in older adults. Note that under the certainty-effect account, no such difference in outcome sensitivity between these two problems types is expected.

To summarize, we have delineated four mechanisms—complexity aversion, response noise, probability weighting, and outcome sensitivity—that might contribute to the effect of option complexity on age differences in risky choice. Note that each mechanism could affect both age groups, which would be indicated by a main effect of problem type (complex safe) on the respective outcome variable (i.e., model parameters or choice behavior, see Table 2.2). Moreover, the hypotheses predict that each mechanism would be more pronounced in older versus younger adults, which would be indicated by an interaction between complexity and age group on the outcome variable. However, it is also possible that option complexity affects choices through a combination of several mechanisms (except if their predictions are mutually exclusive). For instance, complexity could affect both the processing of probabilities and outcomes, and none, one, or both of these mechanisms could be more pronounced in older adults.

2.2 Study 1

We tested these hypotheses by experimentally manipulating (within-subjects) the complexity of a safe option. The key question was how this manipulation would affect the willingness of younger and older adults to choose a safe option over a risky option. Whereas the complexity-aversion hypothesis can be tested based on the observed choice probabilities alone, testing the response-noise,

Table 2.3: Characteristics of the Participant Sample in Study 1 by Age Group

Characteristic	Younger	Older
n	82	76
Sex (n female)	39	41
Age (years)	$M = 26$, $Md = 25$, $SD = 4.2$	$M = 60.4$, $Md = 60$, $SD = 4.4$
—range	[18; 34]	[55; 72]
Self-reported Risk Preference	$M = 5.9$, $Md = 6$, $SD = 2.2$	$M = 5.4$, $Md = 6$, $SD = 2.2$
Numeracy	$M = 2.6$, $Md = 3$, $SD = 1.2$	$M = 2.3$, $Md = 2$, $SD = 1.2$

the probability-weighting, and the outcome-sensitivity hypotheses requires to separate the evaluation of probability and outcome information from the influence of response error. To this end, we modeled choice data in a Bayesian hierarchical implementation of CPT (described in more detail in the section "Testing the underlying mechanisms: Computational modeling"). In our analyses, we used CPT as a measurement model to disentangle and quantify the effects of complexity on response noise and parameters linked to the systematic impact of attribute information on preferences, namely outcome sensitivity and probability weighting. The role of CPT as a measurement model and potential underpinnings of its parameters in terms of cognitive processing strategies are addressed in the General Discussion in more detail. Finally, we also compared the risky choice behavior in both conditions involving safe options with a condition involving two risky options that do not differ in complexity, and do not include safe outcomes.

2.2.1 Method

Participants

The experiment was conducted online, using Prolific Academic to recruit participants. We targeted younger and older adults based on age range ($18 - 35$ years and ≥ 55 years, respectively) using the Prolific Academic prescreening tool. Hence, only individuals conforming to the specified age ranges were invited to participate. Participants were removed from the sample if they did not complete the survey, or if their age or sex, as identified by the Prolific Academic prescreening tool, diverged from their responses to the demographic questions at the end of the survey. To ensure that participants had read the instructions and understood the task, we asked a simple comprehension question on the same screen frame.[3] Participants who failed this item were excluded from the sample. The final sample of participants consisted of 82 younger adults and 76 older adults. Demographic characteristics, numeracy scores, and self-reported risk preferences are described in Table 2.3. Participants who finished the experiment received a basic payment of 4.20 GBP as well as a performance-contingent monetary bonus. The bonus was determined individually for each participant by randomly selecting one trial and playing out the chosen lottery. The resulting outcome was converted into GBP (with 100 units in the experimental currency E$, in which the outcomes of the options were presented, corresponding to 1 GBP). Participants were informed about this reward scheme before starting the choice task.

Materials

Risky choice task In the main task, participants were presented with a total of 108 two-option choice problems. Each problem consisted of either a safe and a risky option, or two risky options

[3] Specifically, the item read as follows: "To demonstrate that you have understood the task, please indicate which is the correct option below: 1) All gambles involve losses. 2) All gambles involve gains. 3) The equations shown on some gambles express probabilities. 4) The equations shown on some gambles express outcomes." Response 4 was correct.

(depending on condition). 12 choice problems included a stochastically dominated option, in which all outcomes were lower than all outcomes of the other option. We included these problems to assess data quality: Participants who paid attention should choose the dominating option in most of these trials. The main analyses of risk attitude reported below include the nondominated problems only.

In the risky choice task, each option offered monetary outcomes, described in terms of the experimental currency E$ ("E-Dollar"), and the probabilities of these outcomes, expressed as percentages. In half of the choice problems, the more risky option (both in terms of variance and in terms of coefficient of variation, CV; Weber et al., 2004) had a higher expected value; in the other half, the less risky option had a higher expected value. The problem set did not involve choices between equal EV options.This is because only problems with unequal EVs allow to measure decision quality. Moreover, if all options had equal EVs participants would not have an incentive to seriously engage in the task, because their choices would not be consequential. For each problem, participants were asked to indicate which option they preferred and how confident they were in this preference on a 10-point confidence scale ranging from "very confidently A" to "very confidently B," where A and B referred to the options "lottery A" and "lottery B". (In our analyses below, however, we focus on the binary choices.) Screen shots and a timeline for the task can be found in Appendix A.7.

The within-subjects manipulation of option complexity was implemented using three types of choice problems (see Figure 2.1). In all three types, one option was a risky option, offering two possible outcomes with some probability (adding up to 100%). Depending on problem type, this risky option was paired with either a simple safe option, a complex safe option, or another (less) risky option. In the *simple safe condition*, the safe option offered one outcome, expressed as a single number, with certainty (100%). In the *complex safe condition*, the safe option offered the same certain (100%) outcome magnitude as the simple safe condition, but this outcome was expressed as a mathematical term in which two integers had to be multiplied by a number between 0.01 and .99 (rounded to the second digit and adding up to one) and then summed up (see Figure 2.1). For instance, a safe outcome of 66 E$ was expressed as (0.6 x 90) + (0.4 x 30) E$. Finally, in the *risky condition*, both options were risky, but one was more risky than the other. The second risky option was constructed using the same components as in the mathematical term in the complex safe condition: The two integers were used as the outcomes, and the weights as their probabilities (adding up to 100%). For example, the complex safe outcome of (0.6 x 90) + (0.4 x 30) E$ corresponded to a risky option offering 90 E$ with 60% and 30 E$ with 40%. Note that the risky condition and the complex safe condition were structurally similarly complex: In both conditions, calculating each option's objective value required to multiply two sets of numbers and add up the results. The construction principle for the choice problems also ensured that EVs and EV differences were the same across all three conditions. The outcomes were randomly sampled from a uniform distribution ranging from 1 to 100. To prevent participants from recognizing options from a previous choice problem in a different condition, the outcomes of corresponding choice problems were randomly jittered by +/-2 across the conditions. The first outcome's probability was obtained by randomly sampling the uniform distribution ranging from 0.01 to 0.99; the second outcome's probability was the difference between the obtained value and 1. In all three conditions, half of the choice problems involved gain outcomes; the other half, loss outcomes. Choice problems with losses were constructed by reflecting the outcomes of the choice problems with gains into the loss domain. We provide a full list of all choice problems in Appendix A.9, where we also display choice probabilities in younger and older adults on each individual problem.

Every participant made choices in all conditions and both domains. The choice problems were presented in a randomized order that was uniquely determined for each participant. We also randomized which side of the screen the high and low risk options appeared on across choice problems and uniquely for each participant. Response times in the risky choice task were recorded in ms.

Complexity rating In order to measure to what extent the participants perceived the different types of choice problems as differing in complexity, we had them rate the perceived complexity of a subset of 30 randomly drawn choice problems from the different conditions, on a six-point scale ranging from 1 = "very low complexity" to 6 = "very high complexity".

Self-reported risk preference In order to explore how participants' decisions in the three conditions of the risky choice task related to their self-reported risk preference, we asked participants to indicate their risk preference on a one-item general risk question: *How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: "not at all willing to take risks" and the value 10 means: "very willing to take risks".* This is a standard item which has been used, for instance, to assess the risk preferences in the in the German Socio-Economic Panel (SOEP; see Dohmen et al., 2011) and across different age cohorts (Josef et al., 2016).

Berlin Numeracy Test As the more complex choice problems involved more challenging numerical operations, we explored the role of numerical abilities and measured participants' numeracy, using the adaptive, computerized version of the Berlin Numeracy Test (Cokely et al., 2012). This adaptive test consists of two to four items (depending on a person's responses) and is normed to divide participants into quartiles based on their numerical skills.

Design

The experiment had a mixed design, with age group as between-subjects factor and type of choice problem (simple safe, complex safe, and risky) and domain (gains vs. losses) as within-subjects factors. The experiment was approved by the IRB of the Max Planck Institute for Human Development.

Procedure

The experiment was programmed in the survey software Unipark. Participants from the subject pool of Prolific Academic were approached based on age as previously delineated and invited via e-mail. Upon clicking the invitation link, participants were directed to the questionnaire, informed about privacy and data-protection guidelines and asked for informed consent. Participants who did not provide informed consent were not able to proceed to the study. Next, participants received instructions regarding the risky choice task, its baseline payment and incentivization scheme and then completed this task, the complexity rating, and the numeracy task (in that order). After completing all tasks, participants indicated their gender and age in years and answered the self-report item on risk preference. In addition, they had the opportunity to comment on the study in an open-answer written format. Participants then clicked on a link to get redirected to Prolific Academic and communicate that they had completed the study. Submissions were accepted after the data had been checked with regard to the criteria described above, which resulted in participants receiving the basic payment. The bonus payments were determined after all participants had completed the experiment. If the randomly selected trial for a participant happened to be a loss trial, no bonus was paid out.

2.2.2 Results

The behavioral analyses were performed in RStudio (Version 1.1.463) running under macOS 10.14.4. Computational modeling was performed on a Windows server in RStudio (Version 1.1.463) and JAGS-4.3.0. All Bayesian GLMER analyses reported below were implemented using the rstanarm package (Goodrich et al., 2018). Individual effects in GLMERs were considered credible if the 95% posterior interval for the coefficient excluded zero. The posterior intervals, sometimes also referred to as credible intervals, cover the central 95% of the posterior distribution of the estimated coefficients, and can be interpreted as covering the range that includes the true parameter value with 95% probability (cf. Morey et al., 2016). All GLMER analyses were conducted separately for the gain and loss domains, given the evidence for domain specific age differences in risk attitude in the previous literature (Best & Charness, 2015). When reporting the effects of the factor problem type (which has three levels), the simple safe condition serves as the reference condition (unless specified otherwise). In brackets we specify the condition that was compared to the reference condition. For instance, a main effect of problem type (complex safe) reports the comparison between the simple safe and the complex safe condition—that is, the effect of complexity. An interaction between problem type (complex safe) and age group (older) describes whether the difference between the simple safe and the complex safe condition was more pronounced for older than for younger adults—that is, whether older adults showed a stronger response to complexity. For the factor age group the younger adults served as the reference group.

To first assess the quality of the choice data, we inspected the responses in the risky choice problems including a dominated option. Across all problem types, participants chose the dominating option in 69.22% of trials in the domain of gains (average choice proportion for younger adults: 73.96%; older adults: 64.19%) and in 88.46% of trials in the domain of losses (younger adults: 88.82%; older adults: 88.07%). The high overall rate of choices of the dominating option indicates relatively good data quality. Further analyses of the choices on the problems with a dominated option are reported in Appendix A.1.

Was the complexity manipulation successful?

We used Bayesian GLMERs to analyze participants' complexity ratings of the three problem types. Detailed results are reported in Table A.1 and illustrated in Figure A.2 in Appendix A.1. Participants rated the choice problems from the complex safe condition and those from the risky condition as more complex than those from the simple safe condition, indicating that the complexity manipulation was successful.

We also examined the effect of the complexity manipulation on response times (RTs) in the risky choice task, using Bayesian mixed-effect regressions. Detailed results are reported in the bottom panel of Table A.1 and illustrated in Figure A.3 in Appendix A.1. Most importantly, and further supporting that the complexity manipulation successfully increased the complexity of the problems, participants took longer to make choices in the complex safe condition and the risky condition than in the simple safe condition. Further, older adults overall took more time for their choices than younger adults.

Overall, the analyses show that our manipulation increased, as intended, the complexity of the safe options both subjectively (in terms of complexity ratings) and objectively (in terms of the time spent on solving the task).

Did complexity affect age differences in risky choice?

Next, we tested the basic hypothesis about the effects of complexity on behavior in the risky choice task, according to which age differences in risky choice should be reduced or even eliminated in choices between more similarly complex options (for an analysis of decision quality, the tendency to choose the option with the higher EV, see Appendix A.5). The average empirical choice proportions of the less risky option in each problem type, domain, and age group are displayed in the top panel of Figure 2.2. The observed qualitative patterns support the hypothesis: In the condition with simple safe options older adults appear more risk averse in the domain of gains and more risk seeking in the domain of losses. These age differences are attenuated in the other conditions, where options' complexity is more similar.

We next evaluate the statistical credibility of these qualitative patterns. Based on our key hypothesis—according to which older adults are more sensitive to differences in option complexity than younger adults—we expect an interaction between age group and problem type on the tendency to choose the more risky option. To test this hypothesis, we conducted Bayesian mixed-effects logistic regressions using the choice of the more risky option as the outcome variable, and problem type and age group (main effect model) as well as their interaction (interaction model) as fixed effects. The models further included fixed effects for the EV difference between options, a dummy variable indicating whether the option with the higher EV was also more risky, each participant's numeracy score, and their self-reported risk preference. The models included a random intercept for each participant. Coefficients and 95% posterior intervals are displayed in Table 2.4.

In the gain domain, when both options were similarly complex, the tendency to choose the more risky option increased more in older than in younger adults, as indicated by the credible interaction of problem type (complex safe) and age group. This statistically corroborates our basic hypothesis about choice behavior, and the qualitative pattern apparent in Figure 2.2, for the domain of gains: Older adults are more sensitive to differences in option complexity than younger adults. In the loss domain, the interaction between problem type (complex safe) and age group was not credible.

We also conducted a (more liberal) test for the main effect of age group on risky choice behavior within each condition, using Bayesian mixed-effect logistic regressions. Detailed results are reported in Table A.3 in Appendix A.2. To summarize the key findings, in the condition with simple safe options, older adults made credibly more risk-averse choices in the domain of gains, and credibly more risk-seeking choices in the domain of losses, compared to younger adults. No credible differences between younger and older adults emerged in the conditions with similarly complex safe and risky options, in both domains. That is, although in the domain of losses the interaction between problem type (complex safe) and age group was not credible in the model with the full data, the analysis of main effects in the individual conditions extends the support for our core behavioral hypothesis to the domain of losses: Age differences in risky choice behavior are eliminated when both options are similarly complex, in both domains.

Testing the underlying mechanisms: Complexity aversion

The choice patterns are also informative regarding one potential mechanism underlying the effect of complexity on risky choice—the complexity-aversion hypothesis. To recap, according to this hypothesis, increasing an option's complexity should make it *less* attractive, both in the gain and loss domains. To test this hypothesis, we evaluated the direction of the effect of the complexity manipulation on risky choice behavior within each age group, using Bayesian logistic mixed-effect regressions. Detailed results are reported in Table A.5 in Appendix A.2.

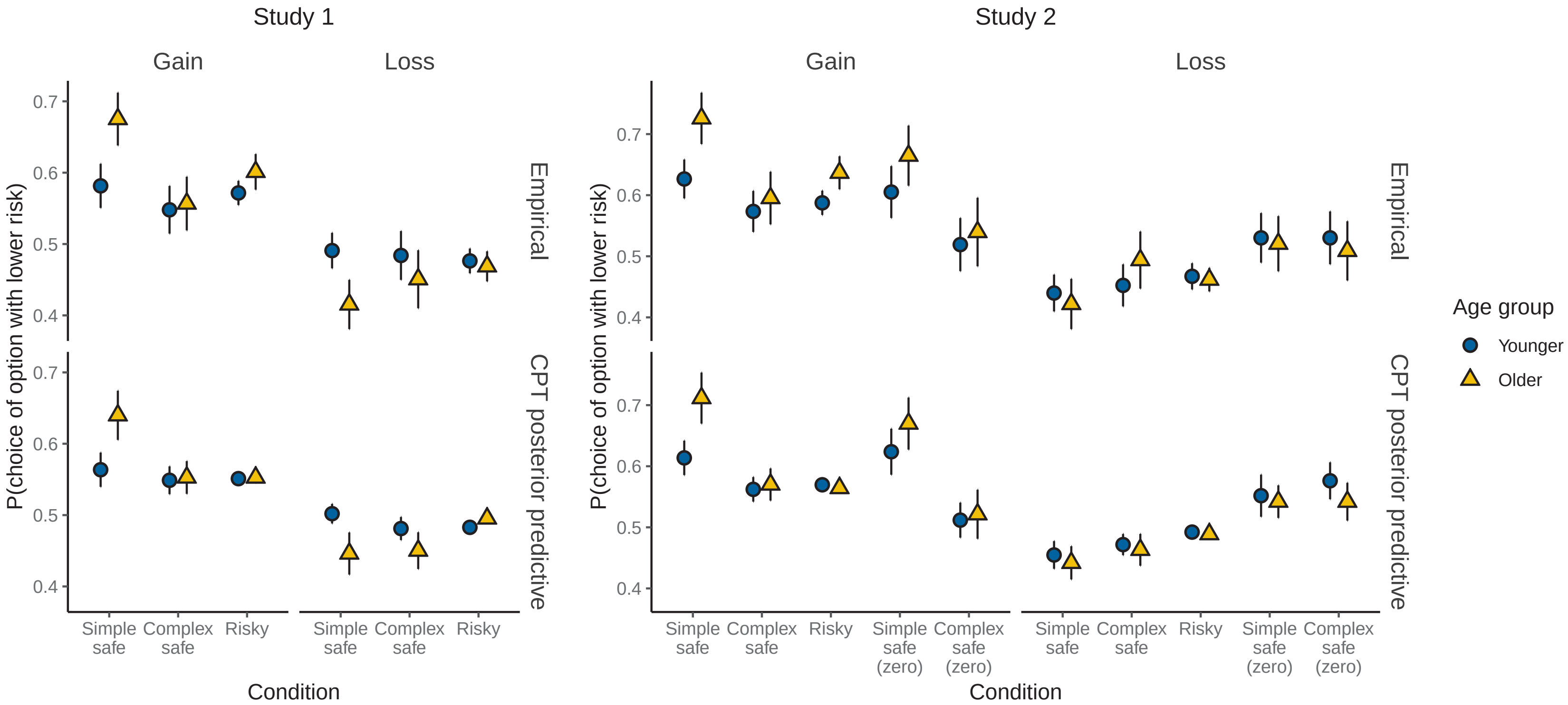

Figure 2.2: Empirical and posterior predictive—that is, predicted by cumulative prospect theory (CPT) based on the estimated parameters—choice proportions for the nondominated problems in all conditions and age groups by domain. Error bars indicate 95% confidence intervals. Age differences in the tendency to choose the low risk option are more pronounced in the simple problem type, where the options differ considerably in complexity, than in problems involving more similarly complex options.

Table 2.4: Regression Coefficients and 95% Posterior Intervals from the Bayesian Mixed-Effects Logistic Regression for Responses in the Risky Choice Task, by Condition, in Study 1 (Upper Table) and in Study 2 (Lower Table). CPT = Cumulative Prospect Theory

Outcome Variable: Choice of Option with Higher Risk (Study 1)	Main effect model		Interaction model		Interaction model with CPT	
Predictor	Gain	Loss	Gain	Loss	Gain	Loss
(Intercept)	**-2.69 [-3.09, -2.28]**	-0.18 [-0.48, 0.12]	**-2.55 [-2.95, -2.16]**	-0.26 [-0.57, 0.04]	**-4.14 [-4.51, -3.75]**	**1.6 [1.26, 1.95]**
Problem Type (Complex Safe)	**0.42 [0.29, 0.56]**	-0.06 [-0.18, 0.06]	0.19 [0, 0.37]	0.03 [-0.14, 0.2]	**-1.07 [-1.33, -0.81]**	**0.42 [0.23, 0.62]**
Problem Type (Risky)	**0.23 [0.1, 0.37]**	-0.08 [-0.2, 0.04]	0.06 [-0.13, 0.24]	0.07 [-0.1, 0.24]	**-0.76 [-1.04, -0.48]**	**0.3 [0.05, 0.55]**
Age Group (Older)	-0.19 [-0.38, 0.01]	**0.16 [0.01, 0.3]**	**-0.48 [-0.72, -0.23]**	**0.32 [0.13, 0.52]**	**-0.42 [-0.63, -0.21]**	0.08 [-0.1, 0.26]
Higher EV Choice = Higher CV Choice	**2.29 [2.18, 2.41]**	**1.23 [1.13, 1.33]**	**2.29 [2.18, 2.41]**	**1.23 [1.14, 1.32]**	**2.36 [2.25, 2.48]**	**1.26 [1.16, 1.35]**
EV Difference	**0.02 [0.01, 0.02]**	-0.01 [-0.01, 0]	**0.02 [0.01, 0.02]**	-0.01 [-0.01, 0]	**0.02 [0.01, 0.02]**	-0.01 [-0.01, 0]
Numeracy	**0.15 [0.07, 0.23]**	-0.03 [-0.1, 0.03]	**0.15 [0.07, 0.24]**	-0.03 [-0.1, 0.03]	0.05 [0, 0.1]	0 [-0.04, 0.05]
Self-reported Risk Preference	0.02 [-0.03, 0.06]	-0.01 [-0.04, 0.03]	0.02 [-0.02, 0.06]	-0.01 [-0.04, 0.03]	-0.01 [-0.03, 0.02]	0 [-0.03, 0.02]
Gender (Male)	**0.18 [0.01, 0.37]**	-0.09 [-0.24, 0.06]	0.18 [0, 0.37]	-0.09 [-0.24, 0.06]	0.08 [-0.04, 0.19]	0.01 [-0.1, 0.11]
Problem Type (Complex Safe) × Age Group (Older)			**0.5 [0.22, 0.77]**	-0.19 [-0.43, 0.05]	**0.58 [0.3, 0.87]**	**0.37 [0.11, 0.63]**
Problem Type (Risky) × Age Group (Older)			**0.38 [0.11, 0.65]**	**-0.31 [-0.55, -0.07]**	**0.44 [0.16, 0.72]**	0.12 [-0.12, 0.37]
Probability Weighting					**1.85 [1.62, 2.08]**	**-1.52 [-1.8, -1.24]**
Response Noise					**-1.27 [-2.24, -0.27]**	**1.09 [0.62, 1.58]**
Outcome Sensitivity					**1.16 [0.96, 1.35]**	**-0.85 [-0.99, -0.7]**

Outcome Variable: Choice of Option with Higher Risk (Study 2)	Main effect model		Interaction model		Interaction model with CPT	
Predictor	Gain	Loss	Gain	Loss	Gain	Loss
(Intercept)	**-2.94 [-3.35, -2.49]**	**-0.61 [-1.02, -0.2]**	**-2.78 [-3.22, -2.36]**	**-0.65 [-1.07, -0.23]**	**-4.48 [-4.79, -4.15]**	**1.35 [0.98, 1.73]**
Problem Type (Simple Safe Zero)	**0.29 [0.12, 0.45]**	**-0.43 [-0.59, -0.27]**	0.16 [-0.05, 0.36]	**-0.4 [-0.6, -0.2]**	0.23 [0, 0.47]	-0.09 [-0.35, 0.16]
Problem Type (Complex Safe)	**0.53 [0.4, 0.67]**	**-0.24 [-0.36, -0.11]**	**0.3 [0.1, 0.48]**	-0.07 [-0.25, 0.11]	0.11 [-0.08, 0.29]	0.17 [-0.02, 0.36]
Problem Type (Complex Safe Zero)	**0.87 [0.71, 1.03]**	**-0.39 [-0.56, -0.24]**	**0.62 [0.42, 0.83]**	**-0.4 [-0.61, -0.2]**	-0.09 [-0.3, 0.13]	0.04 [-0.18, 0.26]
Problem Type (Risky)	**0.37 [0.24, 0.51]**	**-0.19 [-0.32, -0.06]**	**0.22 [0.04, 0.4]**	-0.15 [-0.34, 0.03]	**0.35 [0.15, 0.56]**	0.21 [0, 0.4]
Age Group (Older)	-0.23 [-0.48, 0.03]	-0.01 [-0.26, 0.24]	**-0.56 [-0.88, -0.26]**	0.09 [-0.21, 0.38]	**-0.7 [-0.92, -0.47]**	**0.27 [0.02, 0.5]**
Higher EV Choice = Higher CV Choice	**2.09 [2, 2.18]**	**2.2 [2.12, 2.29]**	**2.09 [2, 2.18]**	**2.2 [2.12, 2.29]**	**2.19 [2.09, 2.27]**	**2.28 [2.19, 2.37]**
EV Difference	**0.01 [0.01, 0.02]**	-0.01 [-0.01, 0]	**0.01 [0.01, 0.02]**	-0.01 [-0.01, 0]	**0.01 [0.01, 0.02]**	-0.01 [-0.01, 0]
Numeracy	0.11 [-0.01, 0.21]	-0.04 [-0.15, 0.07]	0.11 [0, 0.22]	-0.04 [-0.15, 0.07]	0.06 [0, 0.13]	-0.02 [-0.09, 0.06]
Self-reported Risk Preference	**0.1 [0.04, 0.16]**	0.01 [-0.04, 0.07]	**0.1 [0.04, 0.16]**	0.01 [-0.04, 0.06]	0.03 [0, 0.06]	0 [-0.04, 0.04]
Gender (Male)	0.1 [-0.15, 0.35]	0.13 [-0.1, 0.38]	0.11 [-0.14, 0.35]	0.14 [-0.12, 0.38]	0.05 [-0.09, 0.18]	0.04 [-0.1, 0.2]
Problem Type (Simple Safe Zero) × Age Group (Older)			**0.27 [0.03, 0.53]**	-0.06 [-0.31, 0.19]	**0.47 [0.2, 0.74]**	0.17 [-0.12, 0.45]
Problem Type (Complex Safe) × Age Group (Older)			**0.5 [0.24, 0.77]**	**-0.33 [-0.59, -0.09]**	-0.16 [-0.43, 0.12]	-0.07 [-0.34, 0.19]
Problem Type (Complex Safe Zero) × Age Group (Older)			**0.52 [0.27, 0.78]**	0.01 [-0.24, 0.26]	-0.01 [-0.27, 0.26]	**0.77 [0.47, 1.08]**
Problem Type (Risky) × Age Group (Older)			**0.33 [0.08, 0.6]**	-0.07 [-0.34, 0.19]	**0.47 [0.2, 0.74]**	**-0.51 [-0.8, -0.25]**
Probability Weighting					**1.15 [0.98, 1.32]**	**-0.75 [-0.96, -0.53]**
Response Noise					**-0.24 [-0.32, -0.16]**	-0.04 [-0.19, 0.12]
Outcome Sensitivity					**2.13 [1.95, 2.3]**	**-1.55 [-1.69, -1.41]**

Increasing the complexity of safe options made older adults less likely to choose the safe options in the domain of gains, but not in the domain of losses. On the contrary, there was a slight although non-credible trend indicating that increasing the complexity of safe losses made older adults *more* likely to choose these safe options.[4] That is, while older adults found safe gains *less* attractive when their complexity increased, they found safe losses equally or even more attractive when their complexity increased. This latter result from the domain of losses allows us to discard the complexity-aversion hypothesis, which predicts that increasing an option's complexity should make it *less* attractive, irrespective of outcome domain. We conclude that the higher sensitivity to option complexity of older compared to younger adults is not simply due to more aversion to

[4] In younger adults, increasing the complexity of safe options decreased the tendency to choose these safe options in the domain of gains, but this effect was weaker than in older adults. Younger adults' risky choices were not credibly affected by complexity in the domain of losses.

complexity.

Next, we turn to the remaining candidate mechanisms that we hypothesized might underlie the effect of complexity on risky choice, namely response noise, probability weighting, and outcome sensitivity. We used computational modeling with CPT to evaluate these hypotheses.

Testing the underlying mechanisms: Computational modeling

We modeled participants' choices using a hierarchical Bayesian implementation of CPT. Our model structure is inspired by the implementation in Nilsson et al. (2011, see also Scheibehenne and Pachur, 2015).

In CPT, each option's objective outcomes x_i are transformed into subjective values according to the value function v

$$v(x_i) = \begin{cases} \mathrm{x}_i^{\alpha^{gain}}, & \text{if } \ x_i \geq 0 \\ \text{-}(\mid x_i \mid^{\alpha^{loss}}), & \text{if } \ x_i < 0 \end{cases} \tag{2.1}$$

with $\alpha \in [0, 2]$. The outcome sensitivity parameter α modulates the curvature of the value function and captures the sensitivity to differences in outcomes. $\alpha = 1$ indicates linear (objective) treatment of outcomes and thus high outcome sensitivity. Values of $\alpha < 1$ indicate a concave value function and diminishing sensitivity to outcomes; values of $\alpha > 1$ indicate a convex value function. Note that because our choice problems did not include mixed lotteries, the model's value function does not have a loss aversion parameter.

Further, objective probabilities p are transformed into cumulative decision weights π using the probability weighting function w

$$w(p_i) = \frac{p_i^{\gamma}}{(p_i^{\gamma} + [1 - p_i^{\gamma}])^{1/\gamma}} \tag{2.2}$$

with $\gamma \in [0, 2]$. Whereas Nilsson et al., 2011 implement CPT with non-cumulative decision weights, we defined the decision weights in a cumulative manner, as specified by Tversky and Kahneman, 1992. For a detailed description of how cumulative weights π are derived from w, see Tversky and Kahneman (1992). The parameter γ governs the shape of the probability weighting function and reflects the degree of nonlinear distortion when the probabilities are mapped onto decision weights. The probability weighting function is linear under $\gamma = 1$. Values of $\gamma < 1$ entail an inverse S-shaped probability weighting function; values of $\gamma > 1$ entail an S-shaped probability weighting function. An inverse S-shaped probability weighting function indicates a reduced sensitivity to probabilities in the middle range and a relative amplification of extreme probabilities—thus accommodating the certainty effect. An S-shaped probability weighting function, in contrast, indicates a reduced sensitivity at the extreme ends of the probability scale and a relative amplification of differences in probabilities in the middle range of the scale.

The overall valuation V of each option is then determined by multiplying the subjective values of its outcomes by the corresponding decision weights, and then summing up across the outcomes within each option:

$$V = \sum \pi(p_i) v(x_i) \tag{2.3}$$

Choice probabilities are then derived from the valuations of options A and B using the logit choice rule (cf. Stott, 2006), which defines the probability that option A is chosen over option

B as

$$p(A, B) = \frac{1}{1 + e^{-\rho[V(A) - V(B)]}} \tag{2.4}$$

The response noise parameter $\rho > 0$ captures the extent to which choices deterministically follow the difference in valuation between the options. With $\rho = 0$ the choice probability is 0.5 (i.e., choice behavior is not a function of the valuations of the options). With increasing values of ρ the probability of choosing the option with the higher valuation approaches 1. We defined each model parameter (α, γ and ρ) separately for the gain and loss domain, based on the observation that the effects of complexity on the behavioral level are not identical across domains. The chosen model structure made it possible to capture underlying differences in model parameters between the domains.

In Bayesian parameter estimation, parameters are initially represented in terms of prior distributions and then updated into posterior distributions in the light of the observed data. In the hierarchical approach, model parameters are estimated for each participant individually and the individual-level parameters are assumed to be drawn from a group-level distribution. This approach acknowledges dependencies between individual data points due to common sources of variation (M. D. Lee, 2011; Nilsson et al., 2011). We estimated the individual-level and group-level posterior distributions for all parameters, separately for younger and older adults, and for the different conditions of the complexity manipulation in both studies. The CPT model was implemented in JAGS-4.3.0 and estimated using the jags.parallel function from the R2jags package (Su & Yajima, 2015). We ran 30 parallel chains of 101,000 samples each, each including an initial burn-in period of 1,000 samples that were discarded from analysis (cf. Kruschke, 2014). To reduce autocorrelation, the chains were thinned such that every 20th sample was recorded. We assessed convergence via the potential scale reduction factor $\hat{R}$ (Gelman & Rubin, 1992), which was smaller than 1.03 for all estimated parameters, indicating good convergence. To assess whether our computational modeling approach could disentangle the various components of CPT we also conducted an extensive parameter recovery analysis. The analysis demonstrated very good recoverability of the parameters and is reported in Appendix A.8.

To assess the degree to which the estimated CPT model captured the empirical choice patterns, we inspected the posterior predictive choice probabilities based on the posterior estimates of the CPT parameters for each condition, domain, and participant. Both in terms of risk attitude (the tendency to choose the less risky option; Figure 2.2) and decision quality (see Appendix A.5), the posterior predictive choice proportions reproduced the qualitative patterns found in the empirical data very well.

To test the predictions of the response-noise hypothesis, the probability-weighting hypothesis, and the outcome-sensitivity hypothesis, we conducted a series of Bayesian GLM analyses comparing the individual-level parameter estimates in the different conditions and age groups. Each hypothesis predicts effects of problem type on the respective parameter of the CPT analysis (ρ, γ, and α) in both domains (for a summary of the predictions see Table 2.2). In separate Bayesian GLMs, we first analyzed the effects of age group and problem type on the means of the individual-level posterior distributions of each parameter (main effect models). To further test whether older adults were more sensitive to the complexity manipulation than younger adults on any parameter, we calculated a second set of models that also included the interaction between age group and problem type (interaction models). For the models reported in the main text, we used the condition with simple safe options as the reference condition for the problem type

Table 2.5: Regression Coefficients and 95% Posterior Intervals for the GLMs Predicting Parameters of the CPT Analysis in Study 1

Outcome Variable (Study 1)	Gain		Loss	
Predictor	Main effect model	Interaction model	Main effect model	Interaction model
ρ (response noise)				
(Intercept)	**0.2 [0.19, 0.21]**	**0.2 [0.19, 0.22]**	**0.27 [0.25, 0.29]**	**0.28 [0.26, 0.31]**
Age Group (Older)	**-0.03 [-0.04, -0.02]**	**-0.04 [-0.06, -0.02]**	**-0.07 [-0.09, -0.05]**	**-0.09 [-0.13, -0.06]**
Problem Type (Complex Safe)	**-0.1 [-0.11, -0.09]**	**-0.12 [-0.13, -0.1]**	**-0.09 [-0.12, -0.07]**	**-0.12 [-0.16, -0.09]**
Problem Type (Complex Safe) × Age Group (Older)		**0.04 [0.01, 0.06]**		**0.06 [0.01, 0.11]**
Problem Type (Risky)	**-0.03 [-0.05, -0.02]**	**-0.03 [-0.05, -0.01]**	**-0.08 [-0.11, -0.06]**	**-0.09 [-0.13, -0.06]**
Problem Type (Risky) × Age Group (Older)		-0.01 [-0.03, 0.02]		0.02 [-0.03, 0.07]
γ (probability weighting)				
(Intercept)	**0.77 [0.72, 0.82]**	**0.71 [0.64, 0.77]**	**0.78 [0.74, 0.82]**	**0.84 [0.79, 0.89]**
Age Group (Older)	-0.06 [-0.11, 0]	0.08 [-0.01, 0.17]	-0.02 [-0.06, 0.02]	**-0.16 [-0.22, -0.09]**
Problem Type (Complex Safe)	**0.44 [0.37, 0.5]**	**0.51 [0.43, 0.6]**	**0.39 [0.34, 0.44]**	**0.23 [0.17, 0.3]**
Problem Type (Complex Safe) × Age Group (Older)		**-0.16 [-0.28, -0.03]**		**0.33 [0.23, 0.43]**
Problem Type (Risky)	**0.61 [0.55, 0.68]**	**0.73 [0.64, 0.82]**	**0.49 [0.44, 0.55]**	**0.46 [0.4, 0.53]**
Problem Type (Risky) × Age Group (Older)		**-0.25 [-0.38, -0.12]**		0.07 [-0.03, 0.16]
α (outcome sensitivity)				
(Intercept)	**0.72 [0.66, 0.77]**	**0.81 [0.75, 0.87]**	**1.17 [1.11, 1.23]**	**1.26 [1.18, 1.33]**
Age Group (Older)	**-0.1 [-0.15, -0.04]**	**-0.29 [-0.38, -0.2]**	0.02 [-0.05, 0.08]	**-0.17 [-0.28, -0.06]**
Problem Type (Complex Safe)	**0.24 [0.18, 0.31]**	**0.12 [0.03, 0.21]**	-0.06 [-0.14, 0.02]	**-0.12 [-0.23, -0.01]**
Problem Type (Complex Safe) × Age Group (Older)		**0.25 [0.12, 0.38]**		0.13 [-0.03, 0.29]
Problem Type (Risky)	**-0.32 [-0.39, -0.26]**	**-0.49 [-0.58, -0.39]**	**-0.46 [-0.54, -0.38]**	**-0.66 [-0.77, -0.56]**
Problem Type (Risky) × Age Group (Older)		**0.35 [0.22, 0.48]**		**0.42 [0.27, 0.57]**

factor. Comparing the problem type (complex safe) with this reference allowed us to evaluate the effects of complexity on the model parameters predicted by the response-noise hypothesis, the probability-weighting hypothesis, and the outcome-sensitivity hypothesis.

The means of the individual-level posterior distributions for each parameter of the CPT analysis are shown in Figure 2.3 and the resulting value and weighting functions are shown in Figure 2.4 and 2.5. The regression results testing the effect of complexity on CPT parameters are displayed in Table 2.5.

We also tested whether the availability of a safe option affected the parameters of the CPT analysis after controlling for complexity, to address predictions from Mather et al.'s (2012) certainty account. To this end, we re-ran the GLM analyses, this time using the condition with complex safe options as the reference condition. The effect of problem type (risky) in these analyses allowed us to evaluate the isolated effect of certainty. The results are reported in detail in Appendix A.4. To summarize the key results, there were credible main effects of the availability of a safe option on all parameters of the CPT analysis (except for the response noise parameter in the domain of losses), and in some cases, also interactions between certainty and age group. That is, even when differences in complexity between safe and risky options are attenuated, the availability of a safe option affects participants' preferences as reflected by CPT.

Response-noise hypothesis According to this hypothesis, complexity increases response noise, and this effect may be more pronounced in older than in younger adults. We tested this hypothesis using Bayesian GLMs with individual-level estimates of the response noise parameter ρ as the

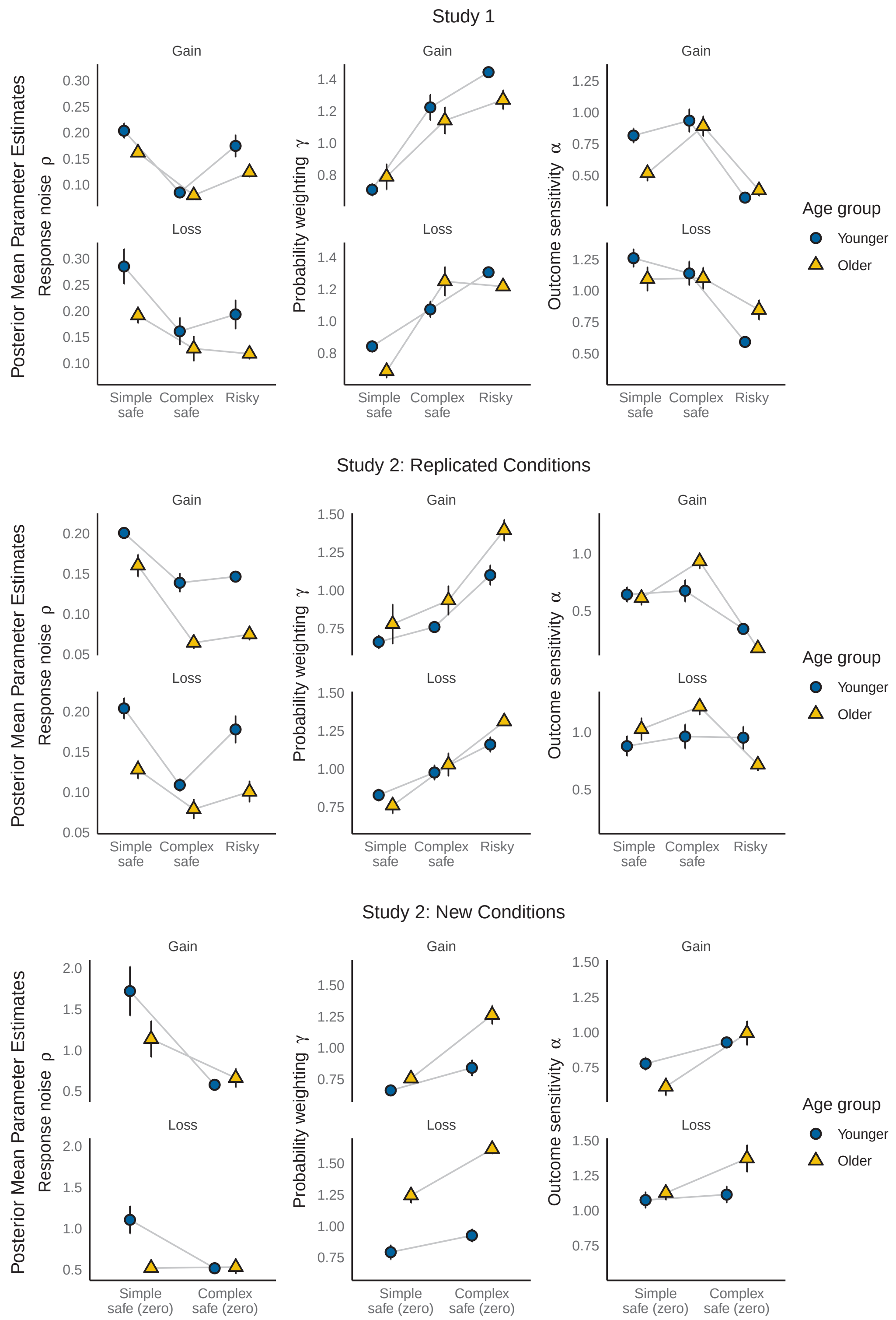

Figure 2.3: Mean and 95% CI of individual-level posterior means for the model parameters ρ (response noise), γ (probability weighting), and α (outcome sensitivity), for each condition and age group, separately for the gain and loss domains.

dependent variable and the simple safe condition as the reference condition for the effect of problem type. GLM results are displayed in Table 2.5. Figure 2.3 displays the means of the estimated individual-level posterior distributions for ρ, for each age group and domain. In both gains and losses, there was a negative main effect of age group, which indicates that ρ was lower and response noise thus higher in older than in younger adults. In both domains, there was also a negative main effect of problem type (complex safe), meaning that for both age groups response noise was higher in the complex safe than in the simple safe condition. Next, we evaluated the interaction model for both domains. In both domains, the interaction between problem type (complex safe) and age group (older) was credible, indicating that younger adults showed a stronger increase in response noise when the safe option was more complex. This might be because older adults already displayed relatively high response noise in the simple safe condition. Taken together, these results support the general notion that choices become more unsystematic when the complexity of safe options increases. This effect was more pronounced in younger than older adults. Response noise alone thus cannot explain the directed effect of complexity on the age differences in risky choice behavior: Increasing the complexity of safe options shifts the proportion of older adults' safe option choices closer to 50%. For the response noise parameter to explain this pattern, the increase in response noise under higher complexity would have to be more pronounced in older adults, in both domains.

Probability-weighting hypothesis According to this hypothesis, differences in option complexity distort the shape of the probability weighting function, and this effect may be more pronounced in older than in younger adults. We hence expected to see a positive effect of problem type (complex safe) on the probability weighting parameter γ in both domains, and a positive interaction of age group and problem type (complex safe). Figure 2.3 displays the means of the individual-level posterior distributions for the γ parameter and Figure 2.4 displays the implied weighting functions for both gains and losses and both age groups. GLM results are displayed in Table 2.5.

In both domains, there was a credible positive main effect of problem type (complex safe) on γ, such that probability weighting functions were less distorted when the second option was a complex safe option than when it was a simple safe option—that is, when the options were more similar in their complexity. The interaction between age group and problem type (complex safe) was credible and negative in the domain of gains and credible and positive in the domain of losses. This indicates that with higher option complexity, younger adults showed a stronger increase in the probability weighting parameter than older adults in the domain of gains, while older adults showed a stronger increase in the probability weighting parameter than younger adults in the domain of losses.

These results support the general notion that probability weighting is more linear when options are similarly complex than when they differ in their complexity. Further, probability weighting can contribute to explaining the (rather small) effects of complexity on the age differences in risky choices behavior in the domain of losses, but not in the domain of gains: For the probability weighting parameter to fully explain the choice patterns, older adults would have to show a stronger increase in the probability weighting parameter in both domains.

Outcome-sensitivity hypothesis According to the outcome-sensitivity hypothesis, increasing the complexity of a safe option increases outcome sensitivity, and this effect may be more pronounced in older than in younger adults. Figure 2.3 displays the means of the individual-level posterior distributions for the outcome sensitivity parameter α and Figure 2.5 shows the corresponding value functions for both domains and age groups. GLM results are displayed in Table 2.5.

There was a positive main effect of complexity on outcome sensitivity in the domain of gains, showing that outcome sensitivity is higher when the safe and risky option are similarly complex than when the options differ in complexity. The negative main effect of age group in the domain of gains indicates that older adults were generally less sensitive to outcome information than younger adults were. This main effect was not credible in the domain of losses. In line with the outcome-sensitivity hypothesis, there was a positive interaction effect of problem type (complex safe) and age group on α in the gain domain, indicating that outcome sensitivity increased more strongly for older adults than for younger adults when both options were similarly complex. This interaction was not credible in the domain of losses.

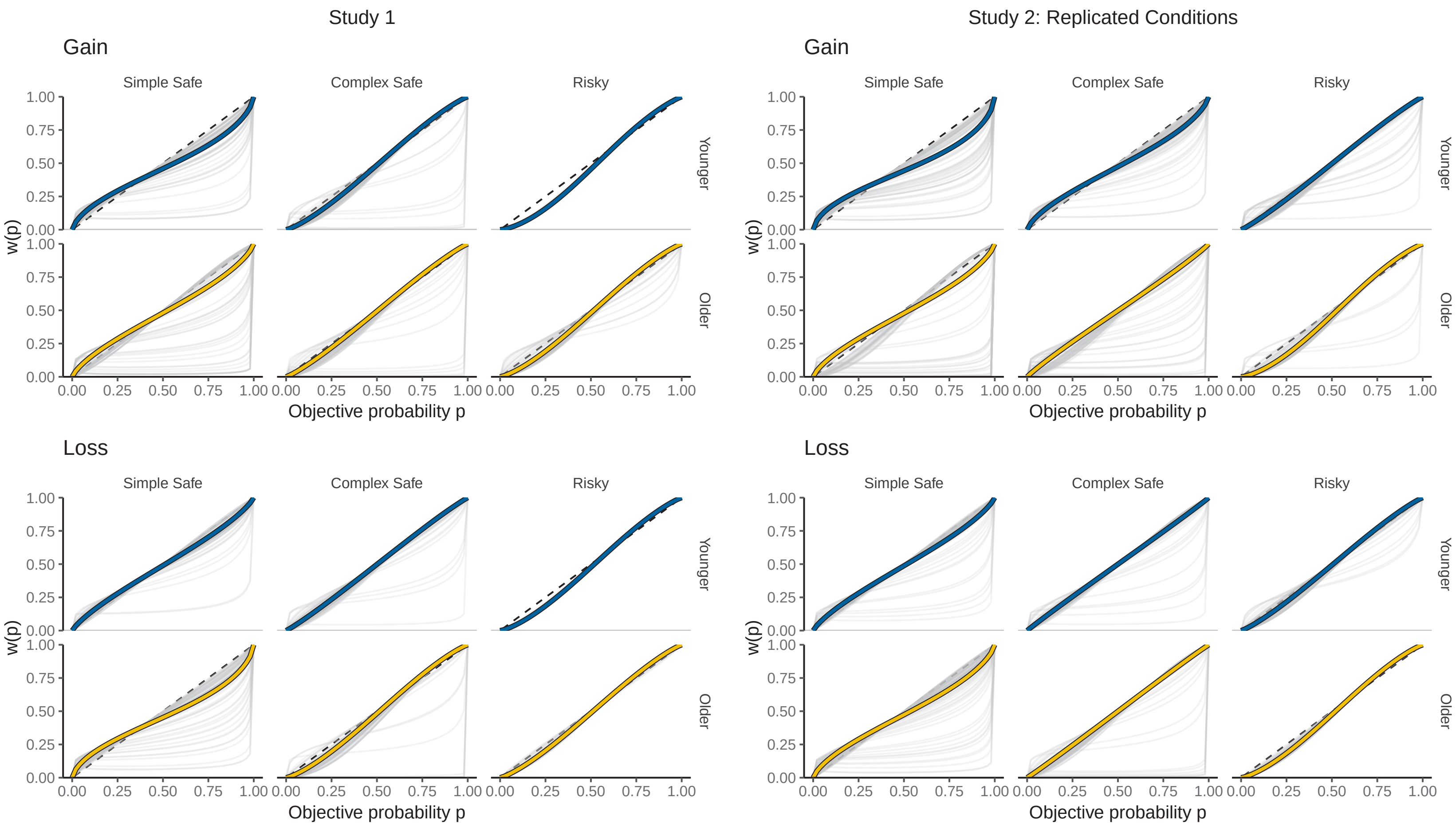

Figure 2.4: Individual-level probability weighting functions (based on CPT probability weighting parameter estimates for gains and losses) for Study 1 and the corresponding conditions that were replicated in Study 2.

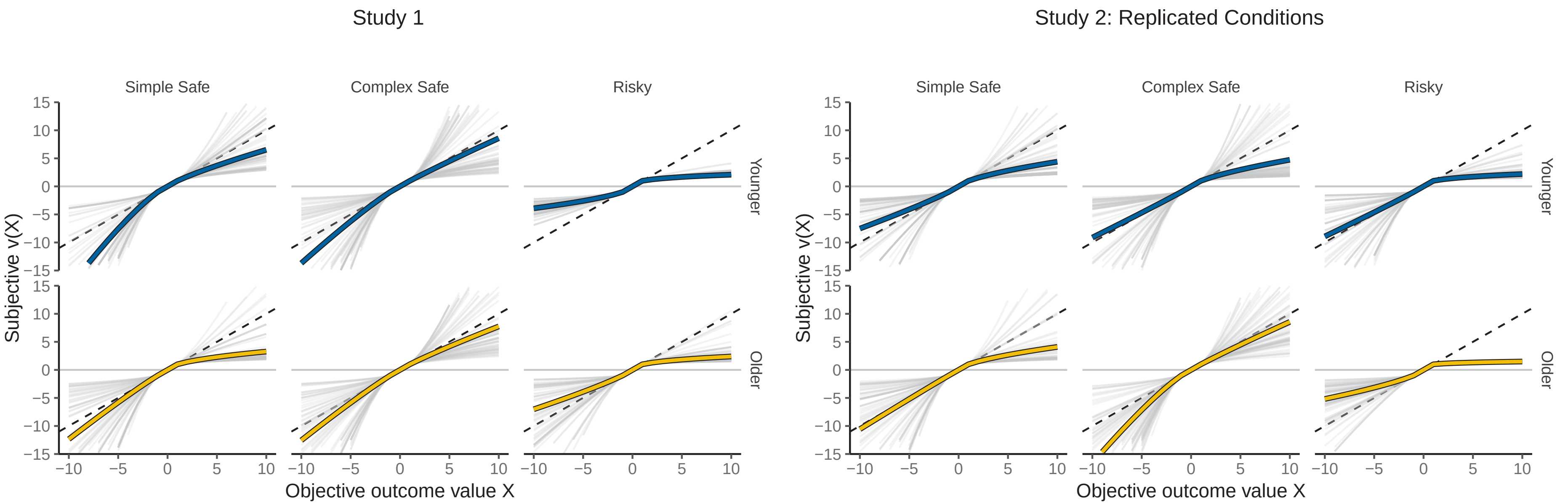

Figure 2.5: Individual-level value functions (based on CPT outcome sensitivity parameter estimates for gains and losses) for Study 1 and the corresponding conditions that were replicated in Study 2.

Outcome sensitivity can thus contribute to explaining the effects of complexity on the age differences in risky choices behavior in the domain of gains, but not losses: For the outcome sensitivity parameter to explain the overall choice patterns, older adults would have to show a stronger increase in the outcome sensitivity in both domains.

Hence, the results on the outcome sensitivity parameter complement our findings on the probability weighting parameter: When the complexity of safe options is increased, older participants show a stronger increase in outcome sensitivity in the domain of gains, and a stronger increase in the probability weighting parameter in the domain of losses, compared to younger adults. Hence, two of our hypotheses about the impact of complexity on age differences in risky choice are supported—indicating that complexity acts via a combination of mechanisms.

Linking the impact of option complexity on age differences in choice to the parameters of the CPT analysis

We next directly linked the observed age differences in risky choice to the differences on the model parameters between conditions and age groups. To this end, we conducted another set of Bayesian logistic GLM analyses to see to what extent the interaction between age group and condition on risk attitude would disappear once the estimated CPT parameters were entered in the regression. The results are displayed in Table 2.4 (interaction model with CPT). As can be seen, the interaction between problem type (complex safe) and age group on risk attitude in the gain domain is still credible when the parameters of the CPT analysis are included in the model. However, all three parameters independently explain some variance in the tendency to choose the high-risk option, and these effects operate in the expected direction.[5]

The observation that all three model parameters—response noise, probability weighting, and outcome sensitivity—contributed to the observed behavioral regularities indicates that complexity acts via a combination of mechanisms.

How do responses in the risky choice task relate to self-reported risk preference?

Finally, we explored the relationship between participants' risky choices and their self-reported risk preferences (as measured with the one-item general risk question). This self-report measure was not related to participants' risky choices in any condition or age group (cf. Table 2.4 and Tables A.3 and A.5 in Appendix A.2). Hence, as in several previous studies (Frey et al., 2017; Pedroni et al., 2017), there was a disconnect between behavioral and self-report measures of risk preference. A Bayesian GLM with self-reported risk preference as the dependent variable and age group and gender as predictors (Table 2.6) shows that despite a slight trend toward a decrease in self-reported risk preference in older adults (consistent with findings in large-scale panel data by Dohmen et al., 2017; Josef et al., 2016), this effect was not credible.

Table 2.6: Regression Coefficients and 95% Posterior Intervals From the GLM of Self-Reported Risk Preference in Study 1 and Study 2

[5] The positive effects of probability weighting and outcome sensitivity in the domain of gains show that higher values on the probability weighting parameter (and thus more linear weighting functions) as well as higher values on the outcome sensitivity parameter (and thus more linear value functions) increased the tendency to choose the risky option. Higher values on the response noise parameter (i.e. lower response noise) decreases the tendency to choose the risky option. In the domain of losses, higher values on the probability weighting parameter and the outcome sensitivity parameter decreased the tendency to choose the risky option. Higher values on the response noise parameter (lower response noise) increased the tendency to choose the risky option.

Outcome Variable: Self-reported Risk Preference (Study 1)	
Predictor	Main Effect Model
(Intercept)	**5.64** **[5.05, 6.21]**
Age Group (Older)	-0.4 [-1.07, 0.29]
Gender (Male)	0.45 [-0.28, 1.15]

Outcome Variable: Self-reported Risk Preference (Study 2)	
Predictor	Main Effect Model
(Intercept)	**4.54** **[3.97, 5.13]**
Age Group (Older)	-0.04 [-0.75, 0.65]
Gender (Male)	**0.7** **[0.01, 1.4]**

2.2.3 Summary of Study 1

Study 1 provided evidence for a crucial role of differences in option complexity between safe and risky options for measuring age differences in risk attitude. As hypothesized, age differences in risky choice behavior emerged in choices with simple safe and more complex risky options, but they were eliminated when safe options were presented in a format similarly complex to risky options. Regarding the underlying mechanism, the results—especially from the domain of losses—speak against the complexity-aversion hypothesis: Increasing the complexity of safe losses did not make them less attractive to younger or older adults. Modeling in CPT reveals that, while higher option complexity increases response noise, this can not explain the behavioral differences between younger and older adults. Rather, older adults' stronger behavioral response to option complexity in the domain of gains was paralleled by a stronger increase in outcome sensitivity, compared to younger adults. In the domain of losses, older adults showed a stronger increase in the probability weighting parameter than younger adults in response to increasing safe options' complexity, indicating increasingly linear weighting functions. These findings suggest that the effect of complexity on age differences on risky choice is driven by a combination of the dynamics captured in the outcome-sensitivity hypothesis and the probability-weighting hypothesis.

2.3 Study 2

Study 1 was an online study. The goal of Study 2 was thus to replicate the results in a laboratory experiment. Therefore, it included the same choice problems as Study 1 to ensure exact replication. Moreover, we extended the investigation of the impact of differences in option complexity on age difference in risky choice to choice problems with a safe option and a risky option that has a zero outcome—a type of choice problem sometimes used in research on age differences in risky choice (e.g. Bruine de Bruin et al., 2007; M. Y. Kim & Kanfer, 2009; Mamerow et al., 2016; Mather et al., 2012; Mikels & Reed, 2009; Rönnlund et al., 2005; Rutledge et al., 2016; Thomas & Millar, 2011; Watanabe & Shibutani, 2010; Weller et al., 2011). In such problems, complexity differences are arguably smaller than in choice problems in which the risky option has no zero outcomes. This is because a risky option with an outcome of zero, for instance offering a 70% chance to win \$50 and a 30% chance to win nothing, that is, \$0, can be reduced to a 70% chance to win \$50. Since the zero outcome and its associated probability can be ignored, the risky option in this type of choice problem is similarly complex to a safe option, for instance offering a 100% chance to win \$40. Consequently, complexity differences between safe and risky options may be comparably small in this problem type, and thus have a comparably small impact on age differences in risky choice—compared to choice problems without a risky outcome of zero (like those used in Study 1). Hence we test if age differences in risky choice also emerge in choice problems with risky outcomes of zero (as found by Bruine de Bruin et al., 2007; M. Y. Kim & Kanfer, 2009; Mather et al., 2012; Rutledge et al., 2016; Watanabe & Shibutani, 2010; Weller et al., 2011), and if so, whether they can also be eliminated by further reducing the complexity differences between the options.

Figure 2.6 illustrates these new choice problems. People are asked to choose between simple safe options and risky outcomes of zero (where differences in complexity are comparably small). Are there age differences on these problems as well, and if so, can they be reduced by increasing the complexity of safe options? Details on the construction of these problems are provided below. To characterize the participant sample and further increase comparability with other prior research, Study 2 also included some additional cognitive and affective measures (more details below).

Figure 2.6: New conditions of the risky choice task in Study 2, including risky options with outcomes of zero.

2.3.1 Method

Participants

The experiment was conducted in the behavioral laboratory of the Max Planck Institute for Human Development in Berlin, and participants were recruited from the internal participant data base of the institute. The sample of participants consisted of 80 younger adults and 80 older adults. We approached participants who were between 18-35 years old or who were at least 60 years old, respectively. Demographic characteristics, self-reported risk preference and cognitive and affective characteristics can be found in Table 2.7. Participants received a baseline payment of €20 and a performance-contingent monetary bonus. Like in Study 1, the bonus was determined individually for each participant by selecting one of the risky choices and playing out the lottery chosen by the participant. To induce a realistic sense of the possibility to win or lose actual money, the experimenter put €5 on the desk in front of the participant as a baseline bonus, before starting the experiment. The experimenter explained that the choices in the experiment would determine if the participant would get to keep this baseline bonus and possibly increase it up to €10, or if they would have to return some of or even the whole baseline bonus at the end of the experiment. After all choice were made, one trial was randomly selected, and the option that the participant had chosen was played out. The resulting outcome was converted into Euros (with 100 units in the experimental currency E$, in which the outcomes of the options were presented, corresponding to €5). The converted amount in € was added to or subtracted from the baseline bonus of €5, depending on whether the randomly selected lottery was a gain or a loss trial. Detailed instructions about this reward scheme were also provided in written form.

Materials

All tasks of Study 2 were programmed in PsychoPy (version 1.85.2).

Table 2.7: Characteristics of the Sample in Study 2 by Age Group. Categories for Monthly Income, in €: (500 or less/500-1000/1000-1500/1500-2000/2000-2500/2500-3000/3000-3500/3500-4000/4000 or more/Not disclosed). Categories for Highest Educational Attainment: (Still In School/Completion of Compulsory Basic Secondary School/Secondary School Degree/High School Degree/Vocational Training/Bachelor Degree/Master Degree/University Diploma/PhD/Other)

Characteristic	Younger	Older
n	80	80
Sex (n female)	42	41
Age (years)	M = 26.2, Md = 26, SD = 3.9	M = 70.2, Md = 69, SD = 4.8
—range	[18; 34]	[61; 84]
Self-reported risk preference	M = 4.9, Md = 5, SD = 2.3	M = 4.8, Md = 5, SD = 2.2
Numeracy	M = 2.2, Md = 2, SD = 1.2	M = 1.6, Md = 1, SD = 1
Positive affect		
—momentary	M = 3.8, Md = 3.8, SD = 1	M = 4.8, Md = 4.8, SD = 1.1
—habitual	M = 4.5, Md = 4.6, SD = 1	M = 5, Md = 5.1, SD = 0.8
Negative affect		
—momentary	M = 1.9, Md = 1.7, SD = 0.8	M = 1.4, Md = 1.2, SD = 0.6
—habitual	M = 2, Md = 1.9, SD = 0.8	M = 1.6, Md = 1.4, SD = 0.7
DSST		
—n accurate	M = 56, Md = 55, SD = 8.2	M = 37.3, Md = 38, SD = 5.3
—% accurate	M = 0.97, Md = 0.97, SD = 0.03	M = 0.98, Md = 0.99, SD = 0.03
Monthly income (n/category)	(23/26/16/6/3/0/0/0/0/6)	(0/5/20/22/10/8/5/2/5/3)
Educational attainment (n/category)	(1/0/3/25/9/30/9/1/2/0)	(0/5/16/16/7/2/4/26/3/1)

Risky choice task In addition to the choice problems from Study 1, we included an additional 80 problems consisting of a safe and a two-outcome risky option in which one outcome was zero (40 from each domain). Half of these additional problems offered a simple safe option (condition *simple safe zero*) and the other half offered a complex safe option (condition *complex safe zero*). That is, the complexity of safe options was manipulated in the same manner as in the original conditions. However, whereas in Study 1 the terms expressing the complex safe outcome did not include zeros, they did in Study 2. For instance, while a safe outcome of 54 might be expressed as (0.4 x 90) + (0.6 x 30) E$ in Study 1, it might be expressed as (0.6 x 90) + (0.4 x 0) E$ in Study 2. This served to render complex safe options and risky options with zero outcomes similarly complex on the structural level. In both new conditions, half of the choice problems involved gain outcomes; the other half, loss outcomes. The numerical structure of the new choice problems was based on the unequal-EV problems in Mather et al., 2012: The choice problems were constructed by fixing both options' EVs. The safe option's outcome equaled its EV, and one of the risky outcomes was set to zero. The non-zero risky outcome was adjusted to conform to the risky option's EV, while varying its probability from 0.01, 0.05, 0.1, 0.2, 0.4, 0.6, 0.8, 0.9, 0.95 to 0.99 across problems. On half of the problems within each condition and domain, the option with the higher EV was safe, and on the other half was risky. For each of these choice problems, we constructed a version with a simple safe option and a version with a complex safe option. A full list of all choice problems used is provided in Appendix A.9. There, we also report choice probabilities in younger and older adults on each individual problem.

Every participant made choices in all conditions and both domains. The choice problems were presented in a randomized order that was uniquely determined for each participant. We also randomized which side of the screen the high and low risk options appeared on across choice problems and uniquely for each participant. Response times in the risky choice task were recorded in ms.

Complexity rating, numeracy test and self-reported risk preference As in Study 1, participants rated the perceived complexity of a subset of 30 randomly drawn choice problems, solved the numeracy test and indicated their self-reported risk preference.

PANAS We also included a measure of momentary and habitual affect, a German version of the 10 item positive-and-negative-affect scale PANAS (Grühn et al., 2010; Watson et al., 1988). On each trial of the PANAS, an adjective describing an affective state was presented in the center of the screen and participants were asked to rate how strongly they felt this affect right now (for momentary or state affect) or generally (for habitual or trait affect). Participants responded on a 7-point scale (see Grühn et al., 2010). There were 2 separate blocks for measuring state (momentary) and trait (habitual) affect, both including the same adjectives. The 10 positive and 10 negative adjectives were presented intermixed and randomized within each block. The order or the two blocks was randomly determined for each participant.

Digit symbol substitution test We also included a measure of fluid intelligence in terms of speed of processing: Participants completed a digit symbol substitution test (cf. McLeod et al., 1982). A table on top of the screen defined a (randomly determined, for each participant) mapping between 9 symbols and the digits 1—9. On each trial, one of the 9 symbols was presented in the center of the screen and participants had to press the associated number key; the next symbol appears as soon as the participant has responded. The test lasted 90 seconds and participants were instructed to work as quickly and as accurately as possible. We report both the number of correctly matched symbol-number pairs and the percentage of correct responses in Table 2.7.

Design

The experiment had a mixed design, with age group as between-subjects factor, and type of choice problem (simple safe, complex safe, risky, and the new conditions simple safe zero and complex safe zero) and domain (gains vs. losses) as within-subjects factors. The experiment was approved by the IRB of the Max Planck Institute for Human Development.

Procedure

Upon arriving at the lab participants were informed about privacy and data-protection guidelines and provided informed consent. Next, participants received instructions regarding the risky choice task and the reward scheme. Participants responded to 5 practice trials (which were non-consequential for the determination of the bonus, and participants were informed about this) before completing the actual choice task. After the choice task, participants completed the complexity rating, the numeracy test, the digit symbol substitution task, and the PANAS. The order of these additional tasks was randomized across participants. After completing all additional tasks, participants indicated their gender, age in years, monthly income, and highest educational attainment, and answered the self-report item on risk preference. In addition, they had the opportunity to comment on the study in an open-answer written format. Upon completing the experiment, the bonus payment amount was automatically determined, and each person received the baseline plus the bonus payment.

2.3.2 Results

We implemented and evaluated all behavioral analyses using the same procedures as in Study 1, and extended them to the two new conditions involving zero outcomes. As in Study 1, an analysis of participants' choices in problems with a dominated option indicated good data quality: Participants chose the dominating option in 76.88% of trials in the domain of gains (younger adults: 85.21%; older adults: 68.54%) and in 88.07% of trials in the domain of losses (younger adults: 93.02%; older adults: 83.12%). Further analyses of the choices on the problems with a dominated option are reported in Appendix A.1.

Was the complexity manipulation successful?

We used Bayesian GLMERs to analyze participants' complexity ratings of the different types of choice problems. Detailed results are reported in Table A.1 and illustrated in Figure A.2 in Appendix A.1. As in Study 1, participants rated the choice problems from the complex safe condition and those from the risky condition as more complex than those from the simple safe condition. We further expected that the availability of a zero outcome would reduce the perceived complexity of risky options, and hence of choice problems involving such risky options. This is supported by the ratings: Problems from the simple safe zero condition were rated to be less complex than problems from the simple safe condition. There were no credible differences between complexity ratings for problems from the complex safe zero condition and the simple safe condition. These results support the notion that risky options with a zero outcome, which are structurally less complex than risky options with only nonzero outcomes, are also perceived as such.

We also examined the effect of the complexity manipulation on response times (RTs) in the risky choice task. Detailed results are reported in the bottom panel of Table A.2 and illustrated in Figure A.3 in Appendix A.1. Participants took more time to make choices in the complex safe condition and the risky condition than in the simple safe condition. Moreover, participants made faster choices in the simple safe zero condition than in the simple safe condition, further supporting that the availability of a zero outcome made the choices less difficult. Older adults overall took more time for their choices than younger adults. An interaction between age group and problem type (complex safe) indicated that older adults' RTs increased more than younger adults' when the complexity of the safe option increased. This holds in both the domain of gains and losses.

Did complexity affect age differences in risky choice?

Next, we used the risky choice task to test whether age differences in risky choice behavior were reduced or even eliminated in choices between similarly complex options. The average empirical choice proportions of the less risky option in each problem type, domain, and age group are displayed in the top panel of Figure 2.2. We first assess the effects of option complexity on age differences in risky choice in the conditions that were included in both studies, before turning to the role of zero outcomes. As can be seen, the observed qualitative patterns in these three conditions support our basic hypothesis, and closely reproduce the findings from Study 1: In the condition with simple safe options in the domain of gains older adults appear more risk averse. These age differences are attenuated in the other conditions, where options are more similarly complex. In the domain of losses, younger and older adults are similarly risk seeking in the condition with simple safe options, and both age groups were more risk neutral in the other conditions with similarly complex options. The increase in safe choices in the complex safe condition compared to the simple safe condition in the domain of losses is more pronounced in older adults. Coefficients and 95% posterior intervals from Bayesian GLMER analyses supporting the statistical credibility of these qualitative patterns are displayed in Table 2.4. Credible interactions between age group and problem type (complex safe) in both domains support our hypothesis that older adults are more sensitive to differences in option complexity than younger adults. This interaction in the domain of losses was not credible in Study 1. Hence, Study 2 provides support for our basic hypothesis that older adults are more sensitive to differences in option complexity between safe and risky options, this time across both domains (though the effect is still stronger for gains than for losses).

We also tested for the main effect of age group on risky choice behavior within each condition, using Bayesian mixed-effect logistic regressions. Detailed results are reported in Table A.4 in Appendix A.2. These analyses further support that age differences in risky choice behavior are reduced or eliminated when both options are similarly complex.

Did complexity affect age differences in risky choice in problems involving zero outcomes?

So far, the results from Study 2 replicate, in an independent participant sample and experimental setting, that age differences in risky choice behavior depend on differences in option complexity between safe and risky options—if the risky options involve two non-zero outcomes. Figure 2.2 displays choice behavior in the new conditions of Study 2, offering risky outcomes of zero. Consistent with the finding that the presence of a risky outcome of zero reduces the perceived complexity of choice problems, there were no age differences on problems with a risky outcome of zero. It is thus not surprising that rendering the options even more similar in their complexity by increasing the complexity of the safe option (problem type complex safe zero) does not affect choices. This finding is consistent with the notion that complexity differences between options drive age differences in risk preference: In choices between safe and risky options of comparable complexity (i.e., in our experiments, all problem types except for the simple safe condition without zero outcomes), we expected and observed very small or no age differences.

To statistically corroborate this qualitative pattern, we changed the reference level for the factor problem type to the *simple safe zero* condition, and re-ran the mixed-effects logistic regressions for risky choice behavior reported above. Coefficients and 95% posterior intervals are displayed in Table A.6 in the Appendix A.3. Indeed, there was no credible interaction between problem type complex safe zero and age group in either domain. Moreover, there was no credible main effect of age group within either condition offering risky outcomes of zero (cf. Table A.4 in Appendix A.2).

To summarize, these results extend the support for the complexity account, according to which age differences in risky choice behavior emerge when the options differ considerably in complexity, but are reduced or eliminated once these differences in complexity are reduced. This finding suggests that age differences observed on the basis of choice problems involving choices between a (simple) safe and a (complex) risky option with two non-zero outcomes may not only reflect age differences in risk attitude, but, to some extent, a stronger response to option complexity in older than in younger adults.

Testing the underlying mechanisms

Like in Study 1, the behavioral patterns can be used to discard the complexity-aversion hypothesis: Increasing the complexity of safe options made older adults more likely to choose safe options in the domain of losses. They found safe options *more* attractive when their complexity increased—which can not be explained under complexity aversion. Detailed results statistically corroborating this findings are reported in Table A.5 in Appendix A.2.

Next, we used computational modeling with the same estimation approach and hierarchical Bayesian implementation of CPT as in Study 1 to evaluate the remaining candidate hypotheses, regarding the effects of option complexity on response noise, probability weighting, and outcome sensitivity. The scale reduction factor $\hat{R}$ (Gelman & Rubin, 1992) was smaller than 1.001 for all estimated parameters, indicating very good convergence. The estimated CPT parameters captured the empirical choice patterns very well, as indicated by the posterior predictive choice probabilities for each condition, domain, and participant (cf. Figure 2.2 and Appendix A.5). The means of the individual-level posterior distributions for each parameter of the CPT analysis are shown in Figure 2.3. The resulting value and weighting functions are shown in Figure 2.4 and 2.5 for the replicated conditions. The value and weighting functions for the new conditions involving risky outcomes of zero are shown in Figure 2.7. The CPT-based hypotheses were again evaluated with a series of Bayesian GLM analyses comparing the individual-level parameter estimates in the different conditions and age groups. The coefficients and 95% highest posterior density intervals for the Bayesian GLMs evaluating these different hypotheses are displayed in Table 2.8. We also tested whether the availability of a safe option affected the parameters of the CPT analysis after controlling for complexity. The results are reported in Appendix A.4.

Replicating results from Study 1, response noise was overall higher in older than in younger adults in both domains, and lower in the problems with complex safe than simple safe options, in the domain of losses. Response noise was not credibly higher in problems with complex safe than simple safe options in the domain of gains, in contrast to Study 1. The interaction between problem type (complex safe) and age group (older) was not credible, indicating that younger and older adults showed similar increases in response noise in choice problems with complex safe rather than simple safe options.

Next, we turn to the probability weighting patterns, which also replicate results from Study 1: Probability weighting functions were less distorted when the problem offered a complex safe option rather than a simple safe option—that is, when the options were more similar in their complexity. The interaction between age group and problem type (complex safe) was credible and positive in the domain of losses. This indicates that older adults showed a stronger increase in the probability weighting parameter than younger adults in the domain of losses. There was no credible interaction between problem type (complex safe) and age group in the domain of gains.

Finally, and further replicating the results from Study 1, outcome sensitivity in the domain of gains was higher when the safe option was complex than when it was simple. In contrast to Study 1, there was also a positive main effect of complexity on outcome sensitivity in the domain of losses. We further replicated the result that outcome sensitivity increased more strongly in older adults than in younger adults when safe and risky options were similarly complex, in the domain of gains, but not in the domain of losses.

In summary, these modeling results extend the support for findings in Study 1 that choices are more unsystematic, probability weighting is more linear, and outcome sensitivity is higher, when safe and risky options are similarly complex than when they differ in their complexity. The results from Study 1 and 2 speak against response noise as an explanation for the effects of option complexity on age differences in risky choice (although option complexity led to more noisy responses overall). Rather, both studies indicate that older participants show a stronger increase in outcome sensitivity in the domain of gains and a stronger increase in the probability-weighting parameter in the domain of losses relative to younger adults, when the complexity of safe options is increased. Outcome sensitivity might thus contribute to explaining the effects of complexity on age differences in risky choice in the domain of gains, but not losses. The probability-weighting estimates complement this finding, since they help to explain the effects of complexity on age differences in risky choice in the domain of losses (rather than gains).

Table 2.8: Regression Coefficients and 95% Posterior Intervals for the GLMs Predicting Parameters of the CPT Analysis in Study 2. Reference Condition: Choices Between Simple Safe Options and Risky Options Without a Zero Outcome

Outcome Variable (Study 2)	Gain		Loss	
Predictor	Main effect model	Interaction model	Main effect model	Interaction model
ρ (response noise)				
(Intercept)	**0.25 [0.16, 0.35]**	**0.2 [0.09, 0.33]**	**0.24 [0.19, 0.29]**	**0.21 [0.14, 0.27]**
Age Group (Older)	**-0.14 [-0.22, -0.06]**	-0.05 [-0.22, 0.13]	**-0.15 [-0.19, -0.11]**	-0.08 [-0.17, 0.01]
Problem Type (Complex Safe Zero)	**0.44 [0.32, 0.56]**	**0.37 [0.2, 0.54]**	**0.35 [0.29, 0.42]**	**0.31 [0.22, 0.4]**
Problem Type (Complex Safe Zero) × Age Group (Older)		0.13 [-0.12, 0.37]		0.09 [-0.03, 0.21]
Problem Type (Complex Safe)	-0.08 [-0.21, 0.04]	-0.07 [-0.24, 0.11]	**-0.07 [-0.14, -0.01]**	**-0.1 [-0.19, -0.01]**
Problem Type (Complex Safe) × Age Group (Older)		-0.03 [-0.27, 0.22]		0.05 [-0.08, 0.18]
Problem Type (Risky)	-0.07 [-0.19, 0.05]	-0.06 [-0.24, 0.11]	-0.03 [-0.09, 0.04]	-0.03 [-0.12, 0.06]
Problem Type (Risky) × Age Group (Older)		-0.03 [-0.27, 0.23]		0 [-0.13, 0.13]
Problem Type (Simple Safe Zero)	**1.25 [1.12, 1.38]**	**1.51 [1.33, 1.69]**	**0.64 [0.57, 0.71]**	**0.9 [0.81, 0.99]**
Problem Type (Simple Safe Zero) × Age Group (Older)		**-0.54 [-0.78, -0.29]**		**-0.51 [-0.63, -0.38]**
γ (probability weighting)				
(Intercept)	**0.61 [0.55, 0.67]**	**0.66 [0.59, 0.74]**	**0.67 [0.62, 0.71]**	**0.83 [0.77, 0.88]**
Age Group (Older)	**0.22 [0.17, 0.26]**	**0.12 [0.02, 0.22]**	**0.25 [0.22, 0.29]**	-0.07 [-0.14, 0.01]
Problem Type (Complex Safe Zero)	**0.33 [0.26, 0.41]**	**0.18 [0.08, 0.28]**	**0.48 [0.42, 0.53]**	**0.1 [0.03, 0.17]**
Problem Type (Complex Safe Zero) × Age Group (Older)		**0.3 [0.16, 0.44]**		**0.75 [0.65, 0.86]**
Problem Type (Complex Safe)	**0.13 [0.05, 0.2]**	0.1 [0, 0.2]	**0.21 [0.15, 0.27]**	**0.15 [0.08, 0.22]**
Problem Type (Complex Safe) × Age Group (Older)		0.06 [-0.08, 0.2]		**0.12 [0.01, 0.22]**
Problem Type (Risky)	**0.53 [0.45, 0.6]**	**0.44 [0.33, 0.54]**	**0.44 [0.38, 0.5]**	**0.33 [0.26, 0.41]**
Problem Type (Risky) × Age Group (Older)		**0.18 [0.04, 0.32]**		**0.22 [0.12, 0.32]**
Problem Type (Simple Safe Zero)	-0.01 [-0.08, 0.06]	0 [-0.1, 0.1]	**0.22 [0.16, 0.28]**	-0.03 [-0.1, 0.04]
Problem Type (Simple Safe Zero) × Age Group (Older)		-0.02 [-0.16, 0.12]		**0.51 [0.41, 0.62]**
α (outcome sensitivity)				
(Intercept)	**0.63 [0.58, 0.68]**	**0.64 [0.58, 0.71]**	**0.9 [0.84, 0.97]**	**0.88 [0.8, 0.96]**
Age Group (Older)	-0.01 [-0.05, 0.03]	-0.03 [-0.12, 0.06]	**0.1 [0.04, 0.15]**	**0.15 [0.03, 0.26]**
Problem Type (Complex Safe Zero)	**0.33 [0.27, 0.4]**	**0.28 [0.19, 0.37]**	**0.29 [0.21, 0.37]**	**0.23 [0.12, 0.35]**
Problem Type (Complex Safe Zero) × Age Group (Older)		0.1 [-0.03, 0.22]		0.11 [-0.05, 0.27]
Problem Type (Complex Safe)	**0.18 [0.11, 0.24]**	0.03 [-0.06, 0.12]	**0.14 [0.06, 0.22]**	0.08 [-0.04, 0.2]
Problem Type (Complex Safe) × Age Group (Older)		**0.29 [0.16, 0.41]**		0.12 [-0.05, 0.28]
Problem Type (Risky)	**-0.37 [-0.44, -0.31]**	**-0.3 [-0.39, -0.21]**	**-0.12 [-0.2, -0.04]**	0.07 [-0.05, 0.19]
Problem Type (Risky) × Age Group (Older)		**-0.14 [-0.27, -0.01]**		**-0.38 [-0.54, -0.22]**
Problem Type (Simple Safe Zero)	0.06 [0, 0.13]	**0.13 [0.05, 0.22]**	**0.15 [0.07, 0.23]**	**0.2 [0.08, 0.31]**
Problem Type (Simple Safe Zero) × Age Group (Older)		**-0.13 [-0.26, -0.01]**		-0.09 [-0.26, 0.07]

Impact of complexity on CPT parameters when the risky option has a zero outcome

We also examined how the complexity of safe options affected CPT parameters when a risky outcome of zero was available, using the new conditions of the choice task. To this end, we changed the reference level for the factor condition to the problem type simple safe zero, and reran the Bayesian GLM analyses of CPT parameters. The coefficients are reported in Table 2.9. The effect of problem type (complex safe zero) in these analyses allows us to evaluate the effect of safe options' complexity, given a risky outcome of zero.

There was a negative credible main effect of problem type (complex safe zero) on ρ in

Table 2.9: Regression Coefficients and 95% Posterior Intervals for the GLMs Predicting Parameters of the CPT Analysis in Study 2. Reference Condition: Choices Between Simple Safe Options and Risky Options Offering a Zero Outcome

Outcome Variable (Study 2)	Gain		Loss	
Predictor	Main effect model	Interaction model	Main effect model	Interaction model
ρ (response noise)				
(Intercept)	**1.49 [1.4, 1.59]**	**1.71 [1.58, 1.83]**	**0.88 [0.83, 0.94]**	**1.1 [1.03, 1.16]**
Age Group (Older)	**-0.14 [-0.21, -0.06]**	**-0.57 [-0.74, -0.4]**	**-0.15 [-0.19, -0.11]**	**-0.58 [-0.67, -0.49]**
Problem Type (Complex Safe Zero)	**-0.81 [-0.93, -0.68]**	**-1.13 [-1.3, -0.96]**	**-0.29 [-0.36, -0.22]**	**-0.58 [-0.67, -0.49]**
Problem Type (Complex Safe Zero) × Age Group (Older)		**0.65 [0.41, 0.9]**		**0.59 [0.46, 0.72]**
Problem Type (Complex Safe)	**-1.32 [-1.45, -1.2]**	**-1.56 [-1.74, -1.39]**	**-0.71 [-0.78, -0.65]**	**-0.99 [-1.08, -0.9]**
Problem Type (Complex Safe) × Age Group (Older)		**0.49 [0.25, 0.73]**		**0.55 [0.42, 0.68]**
Problem Type (Risky)	**-1.31 [-1.44, -1.19]**	**-1.56 [-1.73, -1.38]**	**-0.67 [-0.74, -0.6]**	**-0.92 [-1.01, -0.83]**
Problem Type (Risky) × Age Group (Older)		**0.5 [0.25, 0.74]**		**0.5 [0.37, 0.63]**
Problem Type (Simple Safe)	**-1.24 [-1.37, -1.12]**	**-1.51 [-1.67, -1.33]**	**-0.64 [-0.71, -0.57]**	**-0.89 [-0.98, -0.8]**
Problem Type (Simple Safe) × Age Group (Older)		**0.53 [0.28, 0.77]**		**0.5 [0.37, 0.63]**
γ (probability weighting)				
(Intercept)	**0.6 [0.54, 0.65]**	**0.66 [0.59, 0.73]**	**0.89 [0.84, 0.94]**	**0.79 [0.74, 0.84]**
Age Group (Older)	**0.22 [0.18, 0.27]**	0.09 [-0.01, 0.19]	**0.25 [0.22, 0.29]**	**0.45 [0.37, 0.52]**
Problem Type (Complex Safe Zero)	**0.34 [0.27, 0.41]**	**0.18 [0.08, 0.28]**	**0.25 [0.2, 0.31]**	**0.13 [0.06, 0.2]**
Problem Type (Complex Safe Zero) × Age Group (Older)		**0.33 [0.18, 0.46]**		**0.24 [0.14, 0.34]**
Problem Type (Complex Safe)	**0.14 [0.07, 0.21]**	0.1 [0, 0.2]	-0.02 [-0.08, 0.04]	**0.18 [0.11, 0.25]**
Problem Type (Complex Safe) × Age Group (Older)		0.08 [-0.06, 0.22]		**-0.39 [-0.5, -0.29]**
Problem Type (Risky)	**0.54 [0.47, 0.61]**	**0.44 [0.34, 0.54]**	**0.22 [0.16, 0.28]**	**0.36 [0.29, 0.43]**
Problem Type (Risky) × Age Group (Older)		**0.2 [0.06, 0.34]**		**-0.29 [-0.4, -0.19]**
Problem Type (Simple Safe)	0.01 [-0.06, 0.08]	0 [-0.1, 0.1]	**-0.22 [-0.28, -0.17]**	0.03 [-0.04, 0.1]
Problem Type (Simple Safe) × Age Group (Older)		0.02 [-0.12, 0.17]		**-0.51 [-0.62, -0.41]**
α (outcome sensitivity)				
(Intercept)	**0.7 [0.65, 0.75]**	**0.77 [0.71, 0.83]**	**1.05 [0.99, 1.11]**	**1.08 [0.99, 1.16]**
Age Group (Older)	-0.01 [-0.05, 0.03]	**-0.16 [-0.25, -0.08]**	**0.1 [0.04, 0.15]**	0.05 [-0.07, 0.17]
Problem Type (Complex Safe Zero)	**0.27 [0.2, 0.33]**	**0.15 [0.07, 0.24]**	**0.14 [0.06, 0.23]**	0.04 [-0.08, 0.15]
Problem Type (Complex Safe Zero) × Age Group (Older)		**0.23 [0.11, 0.35]**		**0.21 [0.03, 0.37]**
Problem Type (Complex Safe)	**0.11 [0.05, 0.18]**	**-0.1 [-0.18, -0.01]**	-0.01 [-0.09, 0.07]	-0.11 [-0.23, 0]
Problem Type (Complex Safe) × Age Group (Older)		**0.42 [0.29, 0.54]**		**0.21 [0.05, 0.37]**
Problem Type (Risky)	**-0.43 [-0.5, -0.37]**	**-0.43 [-0.52, -0.34]**	**-0.27 [-0.35, -0.19]**	**-0.13 [-0.24, -0.01]**
Problem Type (Risky) × Age Group (Older)		-0.01 [-0.13, 0.11]		**-0.29 [-0.45, -0.12]**
Problem Type (Simple Safe)	-0.07 [-0.13, 0]	**-0.13 [-0.22, -0.04]**	**-0.15 [-0.23, -0.07]**	**-0.2 [-0.31, -0.09]**
Problem Type (Simple Safe) × Age Group (Older)		**0.13 [0.01, 0.25]**		0.1 [-0.07, 0.25]

both domains, indicating that participants' response noise was higher in choices with complex safe options than with simple safe options, when risky outcomes of zero were available. This effect was more pronounced in younger than in older adults, indicated by a credible interaction in both domains. There was also a positive main effect of problem type (complex safe zero) on γ in both domains, indicating that probability weighting was more linear when the safe option was complex versus simple. Moreover, this effect was more pronounced in older than in younger adults, as indicated by the positive credible interactions between problem type (complex safe zero) and age group in both domains. There was a positive main effect of problem type (complex safe zero) on α in both domains, indicating that outcome sensitivity increased when the safe option was

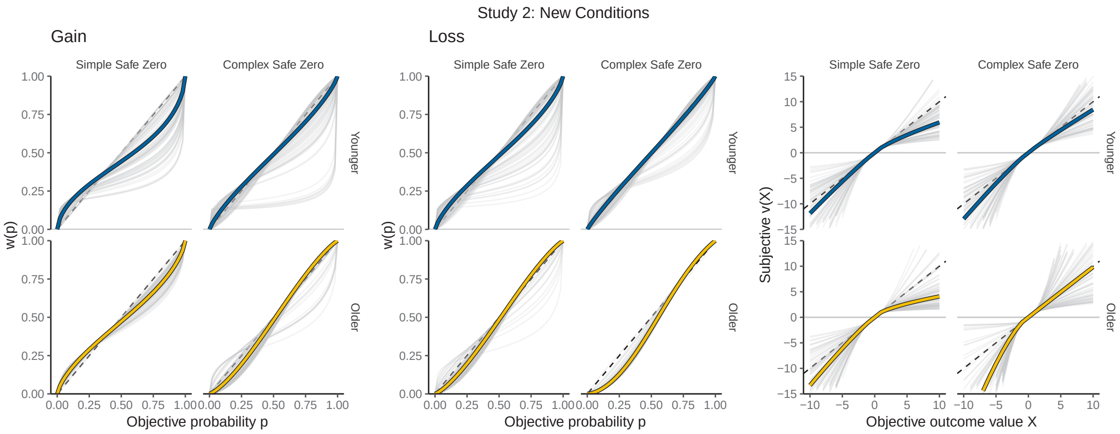

Figure 2.7: Individual-level weighting functions and value functions in the new conditions of study 2, involving risky options with zero outcomes. Value and weighting functions are based on CPT outcome sensitivity parameter estimates and probability weighting parameter estimates for gains and losses.

complex than when it was simple. This effect did not interact with age group. However, there was a positive credible interaction between problem type (complex safe zero) and age group in both domains, suggesting that this effect was more pronounced in older than in younger adults.

Taken together, these results extend the findings from the CPT analyses on the effects of safe options' complexity to choice problems with risky outcomes of zero. Paralleling the results from choice problems without risky outcomes of zero, increasing the complexity of safe options was linked to a decrease in the response noise parameter, and to an increase in both the outcome sensitivity and probability weighting parameters. The effect on response noise was less pronounced in older adults, and the effect on probability weighting was more pronounced in older adults, compared younger adults. That is, in choice problems where risky outcomes of zero were available the interactions between complexity and age group were not credible on the level of choice behavior, but they were on the level of model parameters. This is because computational modeling disentangles in a more fine-grained manner how individual attributes (and distortions thereof) shape choice, and how this differs between age groups and conditions.

Linking the impact of option complexity on age differences in choice to the parameters of the CPT analysis

We next again directly linked the observed age differences in risky choice to the differences on the model parameters between conditions and age groups by conducting another set of Bayesian logistic GLM analyses on risky choice behavior, including the estimated CPT parameters as predictors. The results are displayed in Table 2.4 (interaction model with CPT). Notably, the core finding on the level of choices in both domains—the interaction between problem type (complex safe) and age group on risk attitude—is no longer credible when the parameters of the CPT analysis are included in the model, underlining that the model accounts for these patterns. Moreover, like in Study 1, the observation that all three model parameters—response noise, probability weighting, and outcome sensitivity—contributed to the behavioral regularities to some extent, and in the expected direction, indicates that complexity acts via a combination of factors captured in CPT.

How do responses in the risky choice task relate to self-reported risk preference?

Finally, we again explored the relationship between participants' risky choices and their self-reported risk preferences (cf. Table 2.4 and Table A.4 in Appendix A.2). Higher self-reported risk preference was associated with a higher tendency to choose the risky option in the conditions involving safe options in the domain of gains, but not in the conditions involving two risky options, and not in any conditions in the domain of losses. As in Study 1, there was also no credible main effect of age group on self-reported risk preference (Table 2.6).

2.4 General Discussion

Research in psychology and economics on differences in risk attitude between younger and older adults has yielded not infrequently resulted in conflicting findings. Many studies have concluded that older adults are more risk averse than younger adults (in the gain domain). This pattern, however, has mainly been obtained in tasks involving a choice between a risky and a safe option (Best & Charness, 2015; Mather et al., 2012; Rutledge et al., 2016; Tymula et al., 2013). When choosing between two risky options, by contrast, older adults often appear equally or less risk averse than younger adults (Kellen et al., 2017; Pachur, Mata, et al., 2017). We proposed that age differences in risky choice depend on the availability of a safe option because younger and older adults respond differently to differences in option complexity.

In two studies we varied the complexity of the safe option—thus rendering risky and safe options' complexity more similar —and obtained evidence that age differences in risky choice indeed depend strongly on whether choice problems differ in complexity. Older adults chose more likely a safe gain over a risky one when the two options differed in complexity. This age difference, however, disappeared when these differences were rendered smaller. In Study 1, we also observed find age differences in the loss domain, with older adults now being more likely to choose risky over simple safe losses. However, even these age differences disappeared when complexity differences were rendered smaller. The effect of option complexity on age differences in risky choice could help to explain striking inconsistencies in the literature on age-dependent differences in risk attitude. Moreover, examining the underlying mechanism, we showed that the impact of complexity was not driven by complexity aversion. Using computational modeling with CPT, we found that increasing the complexity of safe options has two somewhat opposing effects: First, it does introduce more error into the choice process. Second, it leads to more 'rational choice' insofar as it increased the sensitivity to differences in outcomes and, in addition, made probability weighting more linear. Finally, we dissociated the effect of option complexity from an effect of certainty: Certainty seems to influence CPT parameters (see Appendix A.4), beyond the effect of complexity. These findings materialized consistently in an online (Study 1) and a laboratory experiment (Study 2). In Study 2, we further found that there were also no age differences in choices between a safe option and a risky option, with the latter offering an outcome of zero and differences in complexity differences being small. Next, we discuss the broader implications of these findings.

2.4.1 Implications for Age Differences in Decision Making Under Risk

Our focus here has been on age differences in risk attitude as revealed in a behavioral task, a commonly used approach to investigate decision making under risk (Hertwig et al., 2019; Mata et al., 2018). Results using this risk elicitation measure have often been interpreted to suggest greater risk aversion in older adults. In contrast our results suggest that these results may be primarily response a response to a property of the anatomy of the stimulus—option complexity.

Once differences in option complexity are render smaller, the age differences in risky choice behavior seem to be reduced or even eliminated.

Let us emphasize, however, that this does not means that younger and older adults are alike in their risky choices outside the laboratory for at least two reasons. The first reason is existing complexity differences in the wild. Specifically, the level of risk in real options may be confounded with complexity, too: For instance, in many situations a safe and easy to evaluate fall-back or default option may be available (e.g., simply maintaining the status quo). Given the effects of option complexity on choice behavior, age differences are likely to emerge in some natural environments but not in others. As a consequence, it may be rather difficult (or even impossible) to predict invariant age differences in behavior in risky situations in general. A more modest, and possibly more promising, approach to predict age differences in risky choice based on behavioral tasks could be to tailor the measurement task to a clearly defined reference class of situations and its contextual features. To this end, it is important to conduct studies like ours, which identify and isolate contextual variables that shape risky choice behavior. The suggested approach also highlights an advantage of behavioral approaches to studying risk preferences: Contextual features of choice tasks can be explicitly varied to match particular target ecologies and to gauge their impact on behavior. The second reason is that age differences have also been found beyond behavioral tasks. Specifically, a second major tradition in measuring risk attitude exists that relies on self-reports. For instance, respondents are asked to indicate on a scale from 0 to 10 how prepared they are to take risks in general (Dohmen et al., 2011). A robust finding in studies using this approach is that older adults indicate a lower willingness to take risks than younger adults (Dohmen et al., 2017; Josef et al., 2016; Mata et al., 2016). It is unclear, however, what situations or episodes of risk taking people use as a basis to inform their response. Although some variants of commonly used self-report items refer to particular domains in life—for instance regarding financial, career, or health risks (Dohmen et al., 2011; Weber et al., 2002)—the self-report approach to measuring risk preferences affords less control over specific contextual features, rendering it difficult to determine their impact.

To summarize, although our understanding of the factors influencing decisions under risk has been growing, it may not be possible to derive a general conclusion regarding age differences in risky choice behavior—simply because decisions under risk are apparently very sensitive to the structural characteristics of the choice ecology. As a consequence, the predictive power of tasks with specific characteristics (e.g., options differing in complexity) may be limited to only those situations that match them. Acknowledging the characteristics' impact may not only enhance predictive power, but also help explain the rather modest convergent validity among diverse behavioral measures (Frey et al., 2017; Pedroni et al., 2017).

2.4.2 Can CPT Parameters be Interpreted Psychologically?

We used the computational modeling framework of CPT to examine potential mechanisms. In implementations with a probabilistic choice rule, CPT separates random error from systematic transformations of the options' attributes. Moreover, CPT distinguishes between a representation of outcome information (value function) and probability information (weighting function), which together are assumed to shape preferences. Our analyses show that participants displayed more linear probability weighting and higher outcome sensitivity in choice problems involving complex safe rather than simple safe options. What can be inferred from these results regarding the impact of option complexity on the underlying cognitive processing?

Possible interpretations in terms of attention

CPT stands in the tradition of "as-if" models of choice, which do not strive to describe the cognitive processes underlying a choice cf. Berg and Gigerenzer, 2010. At the same time, key constructs in CPT, such as "loss aversion", "probability sensitivity", and "outcome sensitivity", have been interpreted psychologically (see Pachur, Suter Hertwig, 2017). Several recent analyses have found evidence that CPT—though not modeling cognitive processes themselves—may be systematically linked to how information is processed. For instance, Pachur et al., 2018 showed that CPT parameters can reflect the amount of attention allocated to probability and outcome information in a construct-coherent manner (e.g., a more linear probability weighting function is associated with more time spent processing probability information). Moreover, Pachur, Suter, et al., 2017 demonstrated that choices simulated based on strategies that ignore probability information are reflected in strongly curved probability weighting functions when modeled with CPT. Finally, probability weighting patterns may reflect asymmetries in the allocation of attention towards individual options in the choice set during preference formation (Zilker & Pachur, 2019).

In light of these results, the observed differences in our CPT analyses between the conditions and age groups might point to specific differences in attention allocation. For instance, the more linear probability weighting and higher outcome sensitivity for choices involving complex safe rather than simple safe options may reflect more attention paid to probability and outcome information, or a more symmetric allocation of attention between safe and risky options. Furthermore, patterns in the allocation and impact of attention on preferences may differ between younger and older adults. Addressing these possibilities directly using process measures (e.g., eye tracking) will be an interesting avenue for future research.

2.4.3 Differential Effects of Complexity in the Gain and Loss Domains

In Study 1 and 2, age differences in response to option complexity primarily emerged in the gain domain, and were substantially attenuated in the loss domain. Specifically, in Study 1, the interaction between complexity and age group on risky choice behavior was credible for gains, but not for losses. In Study 2, this interaction was credible in both domains, but there were no credible age differences in the domain of losses when the safe options were simple.

What might explain this difference across domains? Losses have been shown to trigger an increased investment of cognitive resources and attention. For instance, people maximize more, show longer response times, and search more extensively in tasks involving losses rather than gains (e.g., Lejarraga & Hertwig, 2017; Lejarraga et al., in press; Yechiam & Hochman, 2013). Importantly, this effect might be stronger in older than in younger adults. There is evidence that due to an increasingly unfavourable ratio of gains to losses in later life, older adults undergo a motivational shift in goal orientation and thus focus more strongly on preventing losses rather than on achieving gains (Depping & Freund, 2011). It has also been demonstrated that such an age-specific motivational shift affects risky choice: Best and Freund, 2018 found that older adults are more willing to choose risky options when those options increase the chance of avoiding a larger loss, whereas younger adults are more likely to choose risky options when they offer the chance of larger gains. An increased focus on loss prevention could motivate older adults to invest more effort and cognitive resources specifically in choices about losses—and thus reduce the impact of option complexity. As a consequence, older and younger adults may behave more similarly in choices about losses than in choices about gains.

2.4.4 Effects of Complexity on Age Differences in Other Risky Choice Paradigms

We are not the first to demonstrate that differences in cognitive requirements of a task, for instance due to complexity, affect age differences in risky choice. In their meta-analysis on behavioral risky choice tasks, Mata et al., 2011 concluded that age differences emerged primarily in paradigms with high learning requirements. Older adults also rely more on simpler strategies, which discard certain aspects of information (Mata et al., 2007), especially in choice problems with a high number of options (Besedeš et al., 2012a, 2012b). Moreover, a meta-analysis on pre-decisional information search concluded that older adults search for less information before choice, especially if options were characterized by a greater number of attributes (Mata & Nunes, 2010). Similarly, Frey et al., 2015 investigated the effect of choice set size (2, 4, or 8 options) on age differences in behavior in *decisions from experience*, where participants learn about options by sampling their payoff distributions. The authors found age differences in the effect of higher set size on search effort (older adults sampled less per option than younger adults under high set size) but not in choice behavior. This highlights a subtle but important difference to our study: In contrast to our experiment (where the *options* within a choice problem differed in complexity), Frey et al., 2015 manipulated the complexity of *choice problems* as a whole. Taken together, different facets of complexity in risky choice tasks may impact behavior—and age differences therein—in different ways. Consequently, age differences may emerge in response to some, but not necessarily all manifestations of complexity.

2.4.5 Effects of Complexity on Other Decision Making Phenomena

Our finding that differences in option complexity seem to crucially shape age differences in decision making may also have implications for other prominent decision-making phenomena that are typically demonstrated in tasks with options differing in complexity. One such example are framing effects, and specifically, preference reversals as a result of different descriptions of otherwise numerically equivalent options (Tversky & Kahneman, 1981). For instance, people who appear risk averse in choices about positively framed options often appear risk seeking in choices about (equivalent) negatively framed options. Studies on framing effects often use tasks (e.g., the Asian disease problem; Tversky & Kahneman, 1981) that involve a choice between a safe and a risky option, thus giving ample room to the impact of differences in complexity. A second example is loss aversion, the notion that people assign subjectively greater weight to losses than to gains of the same size (Kahneman et al., 1991; Tversky & Kahneman, 1992). Loss aversion has been invoked to explain the observation that most people reject the chance to play a mixed lottery offering equal chances to lose an amount of money and to win an equivalent of or even larger amount (Gächter et al., 2007; Tom et al., 2007, but see Erev et al., 2008). Importantly, this task also involves a choice between a safe option (i.e., rejecting the risky lottery) and a risky option (i.e., playing the mixed lottery). Finally, option complexity might also affect choices beyond decisions under risk. In intertemporal choice—people are asked to choose between a smaller sooner or a larger later reward—the immediacy effect describes people's tendency to choose the smaller immediate reward (Keren & Roelofsma, 1995; Prelec & Loewenstein, 1991). Immediate rewards, just like safe options, tend to be less complex to evaluate. If so, responses to option complexity—rather than immediacy—might play an not yet recognized role as well in intertemporal choice.

This is admittedly speculative. But it seem pertinent to systematically examine the extent to which responses to option complexity contribute to classical choice phenomena such as framing effects, loss aversion, and immediacy effects. Interestingly, there is already evidence showing that the presence of safe options increases the magnitude of framing effects (Kühberger, 1998) and contributes to the emergence of loss aversion: Many participants show no, or only rather low levels of, loss aversion in choices between two (equally complex) risky gambles (Pachur, Mata, et al., 2017; Pachur et al., 2018; Rieskamp, 2008). Potentially, evidence interpreted as an increased susceptibility of older adults to framing effects (e.g., S. Kim et al., 2005) and an increased loss aversion (Gächter et al., 2007) may, to some extent, reflect their greater sensitivity to complexity.

2.4.6 Conclusion

Do risk preferences differ between younger and older adults? A considerable amount of work in psychology and economics has revealed the constructed nature of preferences (Lichtenstein & Slovic, 2006). To the extent that preferences are constructed, they are likely to be very sensitive to contextual features. It has rarely been considered, however, how older and younger adults may differ in their response to such contextual properties in paradigmatic choice tasks designed to measure risk attitude. We argue that it is essential to acknowledge the influence of subtle task properties on risky choice behavior; otherwise it will remain difficult or even impossible to predict risk behaviors in the wild that are likely to be profoundly impacted by properties of the choice ecology.

2.5 Author Contributions

Author contributions were as follows: V.Z. and T.P. developed the study concept and design. V.Z. programmed the experimental software, designed the stimulus materials and collected the data. V.Z. analysed the data, performed the computational modeling, and interpreted the results. V.Z. wrote the initial draft of the manuscript. V.Z., T.P. and R.H. reviewed and edited the manuscript.

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2.7 Data and Code Availability

Data from both studies and code to implement all analyses is hosted at
https://osf.io/4yts2/?view_only=65b1c240465c48aa9e31512912ae6204

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3 Does Option Complexity Shape Age Differences in Loss Aversion, Framing Effects, and Delay Discounting?

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Abstract

We recently showed that age differences in risky choice behavior, measured based on commonly used choices between safe and risky options which differ in complexity, may be better explained by age differences in the response to differences in option complexity, than by age differences in genuine risk attitude. In other commonly used choice paradigms the options also differ in complexity. Here we investigate whether inferences on age differences in such paradigms—specifically, choice tasks for measuring loss aversion, framing effects, and delay discounting—may also be distorted by complexity differences between the options. In each of these paradigms, we experimentally increased the complexity of the typically simpler option, in order to control for complexity differences. We hypothesized that this manipulation would affect younger and older adults' choice behavior differently. The results indicate no evidence for effects of option complexity on choice behavior that typically considered indicative of loss aversion and framing effects, or for age differences therein. Increasing the complexity of immediate options in delay discounting made younger, but not older adults less likely to choose these options. Our results thus largely disconfirm the hypothesis that differences in option complexity influence age differences in behavior in these choice tasks. We discuss implications and potential explanations for the domain-specificity of complexity effects.

3.1 Introduction

Many classical phenomena of decision making—and by extension, individual differences therein—are typically demonstrated in quite specific choice tasks. For instance, studies on age differences in risk preference have often employed choices between a safe option, which offers a fixed reward amount with 100%, and a risky option, which offers the possibility to win one of two rewards, each associated with a specified probability (p and $1 - p$). In this task, older adults are typically found to be more risk averse in the domain of gains, and more risk seeking in the domain of losses (e.g., Mather et al., 2012; Rutledge et al., 2016).

However, Zilker et al. (2019, see chapter 2) recently demonstrated that older adults' greater tendency to choose safe gains and to reject safe losses may not indicate age differences in proper risk aversion or risk seeking. Rather, these age differences may be due to a previously overlooked confound in the stimulus material: Safe options typically consist of fewer pieces of numerical information than risky options—that is, they are less complex. Zilker et al. (2019, see chapter 2) demonstrated that increasing safe options' complexity, and thus reducing complexity differences between the options, made the commonly observed age differences in risky choice behavior disappear. Hence, behavior that was previously interpreted as age differences in risk attitude is better explained by age differences in the response to option complexity. The authors further demonstrated that this response is not necessarily indicative of complexity aversion, or fully explained by more non-systematic errors, but rather reflects a systematic shift in the impact of attribute information (outcomes and probabilities) on valuation and choice.

Notably, age differences in apparent risk preferences are not the only phenomenon typically demonstrated in choices between options that arguably differ in complexity. Framing effects, loss aversion, and delay discounting—and age differences therein—are other prominent phenomena of this kind. We first describe each phenomenon, the task typically used to demonstrate it (involving a simple and a complex option), and the prior evidence on age differences therein. Then we develop and test hypotheses about the potential role of differences in option complexity in each phenomenon, and about age differences therein. Can age differences in framing effects, loss aversion, and delay discounting be counteracted by reducing complexity differences between the options in the respective choice tasks?

3.1.1 Loss Aversion

Loss aversion describes the observation that *losses loom larger than gains*, that is, losses appear to have a greater impact on choice than gains of equal magnitude (Kahneman & Tversky, 1979). In prospect theory (PT) and cumulative prospect theory (CPT), loss aversion is captured in a value function that is steeper in the domain of losses than in the domain of gains (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Participants' tendency to reject the chance to play a lottery offering equal chances of loosing and winning equivalent amounts of money (Gächter et al., 2007; Tom et al., 2007) is commonly interpreted as evidence for loss aversion. The degree of loss aversion can be measured using choice lists consisting of several such accept/reject choices, where the risky alternative is made increasingly attractive by varying the magnitude of the risky loss outcome (Gächter et al., 2007). Participants with stronger loss aversion are expected to reject more often, even on items where the expected value of the mixed risky gamble is equal to or greater than zero. Note that such accept/reject choices are essentially choices between a mixed domain risky lottery and a safe outcome of zero (the consequence of simply rejecting). The safe option (rejecting) is considerably less complex than the mixed gamble, which consists of several pieces of numerical information (outcomes and probabilities) that can be considered and integrated during valuation. Hence, preferences for the safe option (rejecting) may to some extent reflect a response to these differences in option complexity—not necessarily greater loss aversion. Speaking in favor of this argument, many participants show no loss aversion in choices between two risky gambles (of equal complexity, cf. Pachur et al., 2017; Pachur et al., 2018; Rieskamp, 2008). Furthermore, there is evidence for increased loss aversion in older age (Gächter et al., 2007)—which may to some extent reflect older adults' greater sensitivity to complexity: Older adults may reject mixed lotteries more than younger adults, not (only) because they are more loss averse, but because differences in complexity between the risky lottery and the safe reject choice skew their valuations more. Consistently, in choices between two equally complex risky mixed gambles there is evidence for lower loss aversion in older adults (Pachur et al., 2017).

Hypotheses

We hypothesize that loss aversion may emerge in choices between risky mixed options and safe outcomes of zero. Moreover, increasing the complexity of safe options, thus rendering the two options more similar in their complexity, may reduce the tendency to choose the safe option. This reduction may be more pronounced in older adults, indicating a stronger response to differences in option complexity. These hypotheses are summarized in Table 3.1.

3.1.2 Framing Effects

Whether people tend to choose safe or risky options (which are otherwise equivalent) depends critically on the verbal framing of options in terms of gains or losses. The classical demonstration of framing effects is behavior in the "Asian disease problem" (Tversky & Kahneman, 1981)[1], which requires a choice between different programs in a fictitious scenario where a disease threatens to kill 600 people.[2] In the positively framed condition, the options are described as *"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"* and in the negatively framed condition, the options are described as *"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. Similar to behavioral measures of risk attitude, framing problems typically involve a (simple) safe and a (complex) risky option. The safe option is simpler since it consists of only one certain outcome, compared to the risky option which consists of two possible outcomes and the associated probabilities. These differences in option complexity may contribute to apparent risk aversion in choices about positively framed options (gains) and apparent risk seeking in choices about negatively framed options (losses). Notably, a meta-analysis by Kühberger (1998) concluded that framing effects are stronger in choices between a risky and a safe option (which, in our view, differ in complexity) than in choices between two risky options (which, in our view, are more similar in complexity). This underlines that to some extent, framing effects may be a consequence of complexity differences between the options.

Moreover, a meta-analysis by Best and Charness (2015) demonstrated that younger and older adults differ in their susceptibility to framing effects. This finding is mainly driven by older

[1]Since the original name can be viewed as a manifestation of racial prejudice, now terms such as "deadly disease problem" are sometimes used instead. We only use the original term to clarify which literature we refer to, not to invoke such prejudice.

[2]The precise wording is "*Imagine the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs are as follows:*"

adults' greater propensity to choose (simple) safe options in positively framed problems, compared to younger adults. The age groups behave more alike in negatively framed problems. Note that age differences in the response to option complexity were also more pronounced in choices between gains than losses in the experiments by Zilker et al. (2019, see chapter 2). Hence, it seems plausible that the age differences in choice behavior, especially in positively framed problems, may reflect a stronger response to option complexity in older compared to younger adults.

Hypotheses

We hypothesize that framing effects emerge in choices between the classical simple safe and risky options. Moreover, increasing the complexity of safe options, thus rendering the two options more similar in their complexity, may reduce framing effects. That is, participants may become less likely to choose safe options in positively framed problems, and/or less likely to choose risky options in equivalent negatively framed problems. This reduction in the framing effect may be more pronounced in older adults, due to a stronger response to differences in option complexity. These hypotheses are also summarized in Table 3.1.

Table 3.1: Hypotheses on Potential Effects of Option Complexity on Different Decision Making Phenomena, and on Differences Between Younger and Older Adults.

Choice Phenomenon *Type of Choice Problem*	**Prediction**
Loss aversion	
Simple safe vs. risky	Loss aversion: Unwillingness to choose an advantageous risky option with a potential loss over a safe option of lower value
Complex safe vs. risky	— Reduced loss aversion — Stronger reduction in older adults
Framing effects	
Simple safe vs. risky	Framing effect: Apparent risk aversion in positive frame and apparent risk seeking in negative frame
Complex safe vs. risky	— Reduced framing effect — Stronger reduction in older adults
Intertemporal choice	
Simple immediate vs. delayed	Delay discounting: Preference for smaller immediate (SS) rewards over larger later (LL) rewards
Complex immediate vs. delayed	— Reduced delay discounting — No directed hypothesis about age differences

3.1.3 Delay Discounting

In intertemporal choice, participants are typically asked to choose 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). Preferring SS over LL rewards indicates a tendency to discount the value of rewards conditional on the associated delay. Delay discounting is particularly pronounced in choices between immediate and a delayed rewards, compared to choices between two (more or less) delayed rewards (cf. Berns et al., 2007; McClure et al., 2004). This immediacy effect in intertemporal choice—an overweighting of immediate relative to delayed outcomes—is strikingly analogous to the certainty effect in risky choice—which describes an overweighting of certain relative to probabilistic outcomes (Keren & Roelofsma, 1995; Prelec & Loewenstein, 1991; Weber & Chapman, 2005). Like a certain outcome, the prospect of an immediate reward is very simple to understand. By contrast, delayed rewards often bear implicit uncertainty, making it more difficult to evaluate them: For instance, decision makers may be uncertain whether the delayed reward will actually materialize, and if so, when exactly, or how much utility or hedonic value they will derive from a reward upon its delayed delivery (Dai et al., 2019). Such considerations may render the evaluation of delayed rewards more complex, compared to immediate rewards. Note that the assumed complexity differences between options in intertemporal choice are hence implicit (in the valuation of options), by contrast to the explicit complexity differences (on the level of numerical properties of stimulus materials) in the other investigated choice tasks. Nevertheless, the implicit complexity differences between the options may contribute to the immediacy effect: Preferences for immediate over delayed options may not reflect a genuine attitude towards delays, but—to some extent—a response to implicit complexity differences. The reduced tendency to discount delays in choices between several delayed rewards—which are more similarly complex than immediate and delayed rewards—speaks to this point.

How about age differences in delay discounting? Based on the previous finding that older adults are more likely to choose simple safe over risky gains, compared to younger adults (Mather et al., 2012; Zilker et al., 2019, see chapter 2), one might expect that older adults are also more prone to choosing simple immediate rewards over more complex delayed rewards, compared to younger adults. However, in prior studies on age differences in delay discounting, older adults often behave more patiently than younger adults—that is, they tend to choose delayed rewards more (Eppinger et al., 2012; Green et al., 1994; Green et al., 1999; Li et al., 2013; Löckenhoff et al., 2011; Reimers et al., 2009). In a few other studies, delay discounting behavior appears to be rather stable across the adult lifespan (Green et al., 1996; Samanez-Larkin et al., 2011), and in yet others, older adults are found to discount more than younger adults (Liu et al., 2016; Read & Read, 2004). Hence, prior evidence on age differences in intertemporal choice differs considerably from prior evidence on age differences in framing and loss aversion: Compared to younger adults, older adults seem *less* likely to choose simple immediate rewards over complex delayed ones, while they also seem *more* likely to choose the simple safe options over complex risky ones in the other two paradigms. Hence, it is not clear whether increasing immediate options' complexity might further amplify age differences in intertemporal choice, or attenuate them.

Hypotheses

We hypothesize that people prefer immediate rewards in standard choices between simple smaller immediate and larger later rewards. However, increasing the complexity of immediate rewards, thus rendering immediate and delayed rewards more similar in their implicit complexity, may reduce this tendency to choose immediate rewards. This reduction in apparent delay discounting may differ between the age groups. However, prior evidence points in different directions and thus does not allow to formulate a directed hypothesis about these age differences. These hypotheses are summarized in Table 3.1.

3.1.4 Outline of the Study

We experimentally increased the complexity of safe and immediate options in decision tasks typically used to measure loss aversion, framing effects, and delay discounting. In each case, we investigated whether this manipulation reduced the magnitude of the classical phenomenon, and whether this potential reduction in response to option complexity differed between younger and older adults. We also explore the association between the behavioral 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.

3.2 Methods

3.2.1 Participants

Eighty younger adults (aged 18 - 28, $M = 23.9$, $SD = 2.34$, 39 female) and eighty older adults (aged 61 - 77, $M = 70.8$, $SD = 3.83$, 40 female) participated in the study. Participants were recruited via the internal participant data base of the Max Planck Institute for Human Development, Berlin. The participant sample is characterized in more detail in Table 3.2.

Table 3.2: Characteristics of the Participant Sample. Cognitive Measures, Self-reports and Amount of Bonus Reward Obtained in the Loss Aversion Task.

	Younger adults				**Older adults**			
	M	*(SD)*	*[Min;*	*Max]*	*M*	*(SD)*	*[Min;*	*Max]*
Age (years)	23.9	(2.34)	[18; 28]		70.8	(3.83)	[61; 77]	
DSST								
— % accurate	0.96	(0.03)	[0.83; 1]		0.97	(0.03)	[0.86; 1]	
—n accurate	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								
—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]	
Reward LA (EUR)	3.7	(1.81)	[1; 8]		3.53	(1.71)	[0; 7]	

3.2.2 Choice Tasks

Loss aversion task

To test for the hypothesized effect of differences in option complexity in the behavioral measurement of loss aversion, we constructed a choice task with three conditions. Each condition (called the *simple safe condition, complex safe condition*, and *risky condition*) 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. Each condition involves "distractor" trials which were added for pragmatic reasons (details below).

We based the numerical structure of choice problems on a choice list similar to the one used by Gächter et al. (2007). All option pairs were derived from this list. Each pair on the list consisted of a safe option and a risky mixed option. Each safe option offered an amount of zero for sure and each risky mixed option offered two outcomes, each with a probability of 50%. One outcome of the risky gamble was always 6, and the other outcome varied between trials (possible values being -3, -4, -5, -6, -7, -8, -9). Thus the risky gamble was advantageous and disadvantageous in terms of EV on 3 choices each and equally valuable as the safe outcome of zero on one choice. Hence differences in risk between options were de-correlated from differences in expected value. Loss-averse participants are expected to choose the safe option even if the expected value 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, amounting to a non-negative subjective valuation of the risky option.

We varied the complexity of safe outcomes between the *simple safe condition* and the *complex safe condition*: In the *simple safe condition*, people made choices between a risky mixed gamble (e.g., 50% chance to win 6, 50% chance to lose 5) and a simple safe amount (e.g. 100%

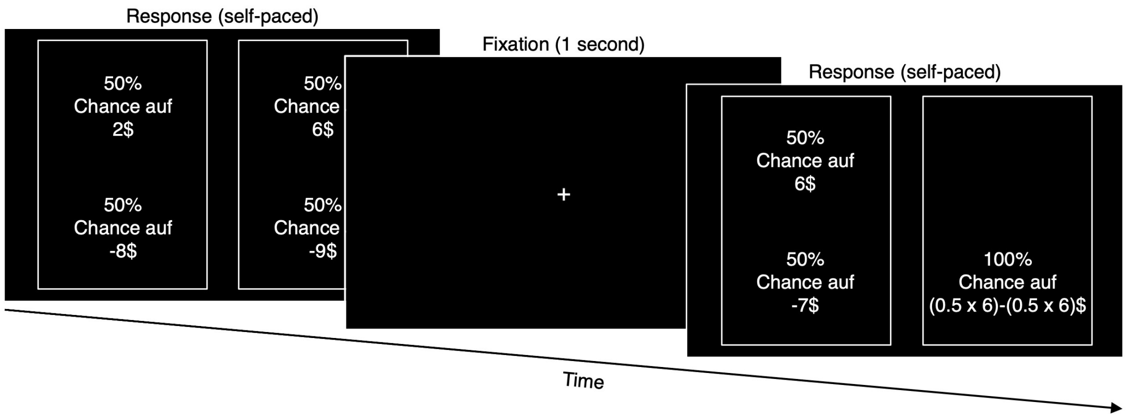

Figure 3.1: Timeline of the loss aversion task with exemplary choice problems. Participants made self-paced choices, separated by a fixation period of 1 second.

chance to win 0). In the *complex safe condition*, people made choices between a risky mixed gamble and a complex safe amount. We manipulated the complexity of safe options analogous to Zilker et al. (2019): In the *complex safe condition*, the safe option offered the same outcome magnitude as in the simple safe condition, but this outcome was now expressed as a mathematical term in which two integers had to be multiplied by .5 and then subtracted. For instance, a safe outcome of -3 could be expressed as a 100% chance to win (0.5 x 2) - (0.5 x 8). The *risky condition*, involved choices between two risky mixed gambles.

Since all safe outcomes in the original choice list were equal to zero, participants might have inferred the value of complex safe options from this regularity, instead of engaging with evaluating the mathematical terms. To make such strategies impossible, the *simple safe condition* and the *complex safe condition* involved *distractor trials*. Distractor trials required choices between mixed risky options and positive or negative safe outcomes (with EVs unequal zero, either -3 or +3). The risky mixed options for distractor trials were the same as those on the original choice list. Both conditions involved 14 such distractor choices (7 with positive and 7 with negative safe outcomes each). In the *complex safe condition* the safe distractor outcomes were displayed in the complex mathematical term format. In the *risky mixed condition*, people made choices between two risky mixed options. The option pairs are based on the risky mixed gambles also used in the other two conditions, and a second risky mixed gamble to replace the respective safe option. These new risky mixed gambles also had probabilities of 50% and the outcomes varied, such that the resulting gambles matched the EVs of the corresponding safe options.

All outcomes were presented in the currency $. Participants were informed that $100 in the experiment corresponded to €5,00 in potential bonus payments (see the section on incentivization for more details). Participants made choices by pressing the keys f and j, corresponding to the left and right option on screen on each given trial.

Framing task

To test for the hypothesized effect of option complexity in framing paradigms, we constructed three types framing problems. We used five framing problems with different cover stories from the previous literature (Chick et al., 2016; Rönnlund et al., 2005). In each condition, participants faced all five problems, framed both positively and negatively (on different trials). The different cover stories involved, for instance, 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 the previous literature these problems often have the same numerical properties (e.g., same number of lives saved/lost) irrespective of the cover story. To avoid such repetition we constructed distinct numerical properties (stakes and probabilities) for each cover story. We ensured to maintain the key characteristic of classical framing problems, namely that both options within each trial always had an equal EV.

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 certain outcome magnitude would be presented in a more complex format. This was achieved by expressing the outcome as a sum of proportions, such as "With certainty 10% of 20 turtles will die, and with certainty 90% of 274 turtles will die". In the *risky mixed 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. Calculating the expected value of the risky option would involve the same numerical operations as calculating the expected value of the complex safe option. Moreover, the expected value of each option was kept constant across the three conditions.

Since individual scenarios were presented repeatedly in different formats and frames (2 frames $\times$ 3 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 the second block of framing trials. Which particular 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 (2 frames $\times$ 3 conditions) were presented in each block. The order of scenarios within each block and the presentation side on screen of the options on each trial was randomized for each participant individually. Participants were instructed to always read each scenario and its options carefully, even though they might appear very similar. It was pointed out that individual scenarios always differed in important respects. Participants were also instructed to read carefully whether percentages (which appeared both in complex safe and risky options) referred to proportions or probabilities.

Participants made choices by pressing the keys 1 and 2, corresponding to the options ("program 1" and "program 2") on each trial.

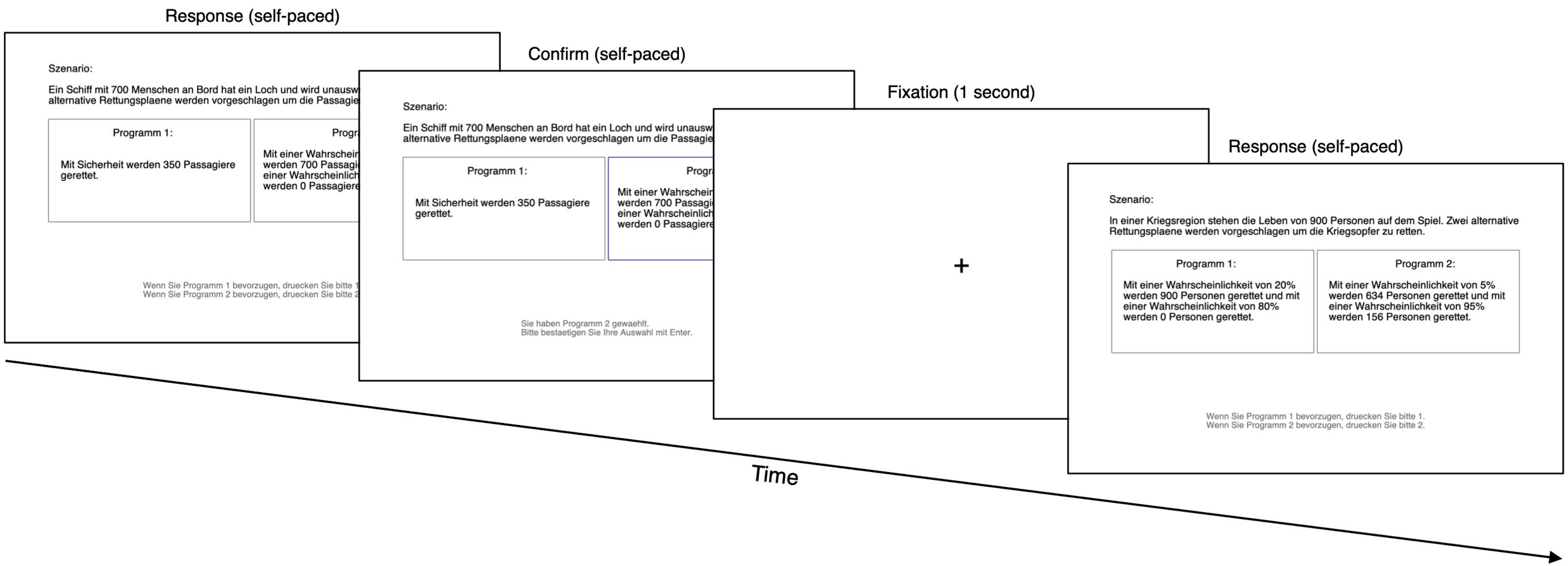

Figure 3.2: Timeline of the framing task with exemplary choice problems. Participants made self-paced choices, confirmed their choices by pressing the Enter key, and moved on to the next scenario after a fixation period of 1 second.

Intertemporal choice task

To test for a possible effect of option complexity differences in intertemporal choice, we constructed a task with three conditions. Each condition involved choices between a smaller sooner and a larger later amount. The *simple immediate condition* involved choices between a simple smaller immediate and a larger delayed reward, such as \$5 today vs. \$10 in 15 days. For the *complex immediate condition* we increased the complexity of the smaller immediate amount used in the simple safe condition by decomposing it into a mathematical term, requiring multiplying a monetary amount by a decimal number. For instance, an immediate reward of 1 in the *simple safe condition* might be described as (0.25×4) in the *complex safe condition.* In the *delayed condition* people made choices between smaller sooner and larger later rewards which were both delayed.

The numerical properties of the choice problems were determined as follows: 10 SS reward amounts were randomly drawn from a uniform distribution ranging from 10 and 200. The 10 associated larger later rewards were generated by increasing the SS rewards by proportions of the SS amount, evenly spaced between 1% and 80%. The resulting 10 pairs of rewards were used in all conditions. To make recurring stimuli less recognizable the SS rewards used in *simple immediate condition* were jittered by +/-1 in the 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 which condition would have the positively or negatively jittered SS reward.

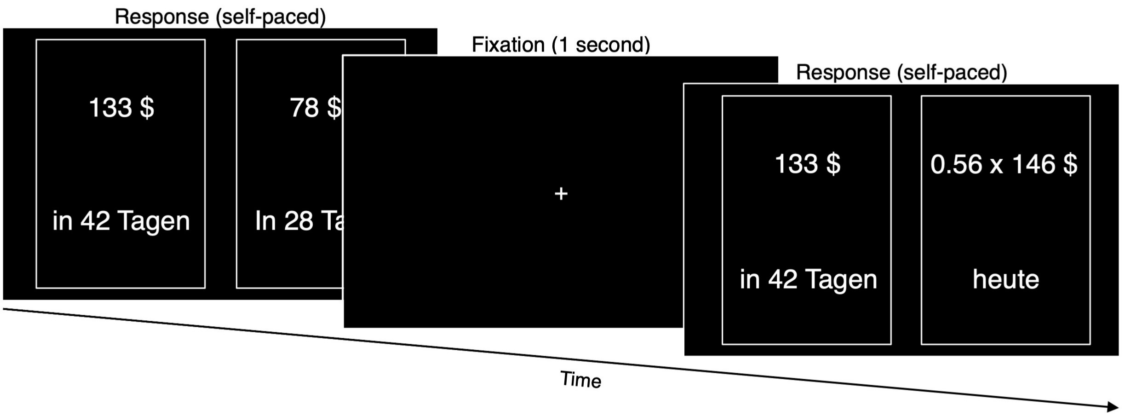

Figure 3.3: Timeline of the intertemporal choice task with exemplary choice problems. Participants made self-paced choices, separated by a fixation period of 1 second.

The delays associated with these rewards were generated as follows: In the *simple immediate condition* and *complex immediate condition* the smaller sooner option was not delayed (verbally described as "today"). In the *delayed condition* the SS reward was always delayed by 14 days (verbally described as "in 14 days"). In each condition there were three possible delays for each LL reward (14 days, 28 days or 42 days after the respective smaller sooner option's delay).[3] That is, each pair of reward amounts occurred at three possible time differences, resulting in 30 choices per condition, and 90 choices in total.

In order to be able to monitor if participants solved the task attentively, we also included attention check trials. On these trials, participants made choices between a *larger* sooner and a smaller later amount. On these trials, the larger sooner amount constituted a dominating alternative that was normatively preferable, both in terms of magnitude and delay. Each condition

[3]Hence the possible delays for larger later rewards in the two conditions with immediate rewards were "in 14 days", "in 28 days" and "in 42 days", and the respective delays for the *delayed condition* were "in 28 days", "in 42 days" and "in 56 days"

included 6 attention check trials.

The rewards in all conditions were expressed in the experimental currency $. Participants were instructed that $100 in the experiment corresponded to €5,00 in real life. Participants made choices by pressing the keys f and j, corresponding to the left and right option on screen on each given trial. The order of trials and the presentation side of SS and LL options on screen within each trial was randomized individually for each participant.

3.2.3 Procedure

Incentivization

Participants received a baseline payment of €20 for participating in the study, and a performance-contingent bonus ranging between €0-€10, determined based on responses in the loss aversion task. Before the start of the experiment, the experimenter put €5 on the desk in front of the participant as a baseline bonus. The experimenter explained that the choices in the first phase of the experiment would determine if the participant would get to keep this baseline bonus and possibly increase it up to €10, or if they would have to return a part of or even the whole amount at the end of the experiment. More detailed instructions about the determination of bonuses were provided in written form as part of the instructions for the loss aversion task. 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 €, such that $100 in the experiment converted to €5 in real bonus payments. The thereby determined bonus amount was added to or subtracted from the baseline bonus of €5, depending on whether the randomly determined trial was a gain trial or a loss trial.

3.2.4 Additional Tasks

Berlin Numeracy Test

We measured participants' statistical numeracy, that is, their understanding of operations of probabilistic and statistical computation, using the 7 item version of the Berlin Numeracy Test (Cokely et al., 2012). The test was scored based on the number of correct responses. The numerical abilities of the younger and older participants are described in Table 3.2.

Digit symbol substitution test

We measured participants' fluid intelligence in terms of a digit symbol substitution test (see McLeod et al., 1982). A table on top of the screen defined a mapping between 9 symbols and the digits 1—9. The mapping was randomly determined for each participant individually. On each trial, one of the 9 symbols was presented in the center of the screen, and participants had to press the associated number key. There was no feedback, and the next symbol appeared as soon as the participant had responded. The test lasted 90 seconds and participants were instructed to work as quickly and accurately as possible. Before the test phase participants practiced the task during 2 practice rounds (9 trials each). We report the fluid abilities of the younger and older participant sample, scored as the total number and percentage of correctly matched symbol-number pairs, in Table 3.2.

Self-reported risk preference, time preference and impulsivity

After completing these cognitive tasks, participants were asked to indicate their introspective risk preference on the one-item general risk question (Dohmen et al., 2011). They were also asked for self-reports regarding their impulsivity and their patience. We used standard items from the German Socio-Economic Panel (SOEP, cf. Richter et al., 2013), which require a response on a discrete 11-point scale. The precise wording of these items is documented in Appendix B.1.

Demographic information

Finally, participants were asked to indicate their age and sex and were 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 lottery and paid the respective amount as well as the baseline participation fee.

3.3 Results

All behavioral analyses were performed in RStudio (Version 1.1.463) running under macOS 10.14.4. All Bayesian GLMER analyses reported below were implemented using the rstanarm package (Goodrich et al., 2018). Individual effects in GLMERs were considered credible if the 95% posterior interval for the coefficient excluded zero. The posterior intervals, sometimes also referred to as credible intervals, cover the central 95% of the posterior distribution of the estimated coefficients, and can be interpreted as covering a range which includes the true parameter value with 95% probability (cf. Morey et al., 2016).

3.3.1 Loss Aversion Task

First, we analyze choice behavior on the non-distractor trials of the loss aversion task, which correspond to commonly used choice lists for measuring loss aversion. We tested the hypothesis that the proportion of disadvantageous safe option choices might decrease when safe options are displayed in a more complex format. We also tested whether such a potential effect of option complexity might be stronger in older adults compared to younger adults.

Figure 3.4 displays the tendency to choose the safe option, conditional on the complexity of the safe option, in trials where the risky option had a higher EV. Remember that loss averse participants are expected to choose the safe option, even if the risky option (which involves the possibility of losses) has a higher EV than the safe option. Hence, the tendency to choose (disadvantageous) safe options on trials where the risky option has the higher EV is typically viewed as indicative of loss aversion. Overall, participants rarely made disadvantageous safe choices, indicating that their behavior was largely driven by EV maximization, and only to a relatively small degree by loss aversion. Moreover, increasing the complexity of safe options did not affect the proportion of disadvantageous safe option choices.

We statistically corroborated these findings by calculating Bayesian logistic GLMERs on the choice of the safe option as the outcome variable, including fixed predictors for age group, the complexity condition, as well as each participant's self-reported risk preference, and a random intercept for each participant (main effect model). We also calculated an analogue model including the interaction between the complexity condition and age group (interaction model). Results are displayed in Table 3.3. Analogous analyses for trials where the safe option had a higher EV—which are not diagnostic regarding loss aversion—are reported in Appendix B.2.

Table 3.3: coefficients and 95% Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Loss Aversion Task, in Non-distractor Trials where the Risky Option had the Higher EV

Outcome: Safe choice (when risky option has higher EV)		
Predictor	Main effect model	Interaction model
(Intercept)	**-2.46** **[-4.04, -1.02]**	**-2.53** **[-4.17, -1.07]**
Age group (older)	0.84 [-0.14, 1.84]	0.9 [-0.13, 1.98]
Condition (complex safe)	-0.19 [-0.59, 0.24]	-0.04 [-0.65, 0.59]
Condition (risky)	**-3.04** **[-3.88, -2.29]**	**-3.57** **[-4.95, -2.42]**
Self-report (risk)	-0.05 [-0.29, 0.2]	-0.05 [-0.3, 0.21]
Age group (older) × Condition (complex safe)		-0.25 [-1.07, 0.52]
Age group (older) × Condition (risky)		0.82 [-0.67, 2.37]

,

There was no credible main effect of condition (complex safe) on the tendency to make disadvantageous safe choices. That is, increasing the complexity of safe options did not affect behavior typically interpreted as indicative of loss aversion. Moreover, there was no credible main effect of age group, indicating that both younger and older adults were equally loss averse. There was a credible negative main effect of condition (risky), indicating that in choices between two risky options (both of which involve the possibility for losses), participants are less likely to chose

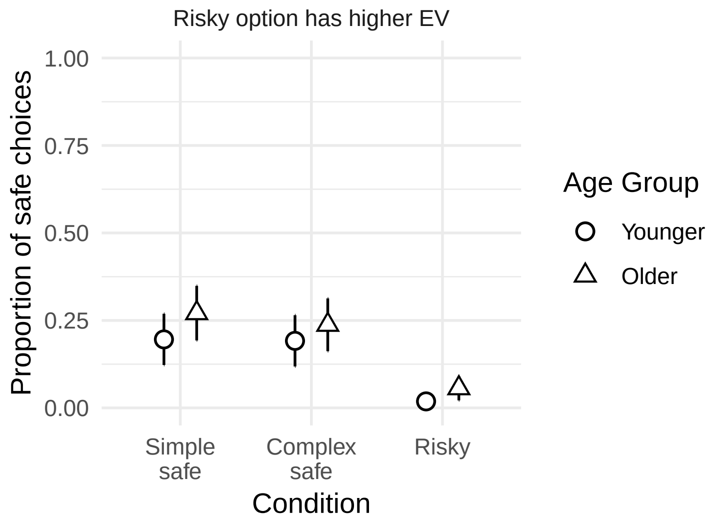

Figure 3.4: Proportion of safe choices in the loss aversion task in non-distractor trials, in which the risky option has a higher EV than the safe option, conditional on the complexity manipulation. Behavior in these trials is most diagnostic regarding loss aversion: Loss-averse participants are expected to choose the safe option—which ensures the avoidance of losses—even though it is disadvantageous since it has a lower EV than the risky option—which offers the possibility of losses. The tendency to make disadvantageous safe choices is unaffected by increasing safe options' complexity, and by age group. In choices between two risky mixed options, the displayed choice proportion is the proportion of choices of the option with the lower risk (rather than the safe option). In these trials both options involve the possibility for losses, and participants made even less disadvantageous low risk choices than if a safe option was available. These patterns emerge in both age groups. Error bars indicate 95 % confidence intervals.

disadvantageous low risk options. That is, since loss aversion makes both options unattractive, they maximize even more. The interaction model further shows that there were no credible interactions between age group and condition, indicating that the age groups were similarly insensitive to the complexity manipulation.

Overall, these results speak against the hypothesis that behavior in choice tasks typically interpreted as indicative of loss aversion depends on complexity differences between the options. Moreover, the results speak against a stronger response to option complexity in older adults in this choice task.

3.3.2 Framing Task

Next we analysed choice behavior on the framing task, displayed in Figure 3.5. Overall, there was a pronounced framing effect in the expected direction: Participants predominantly chose risky options in the negative frame, and predominantly chose safe options in the positive frame.

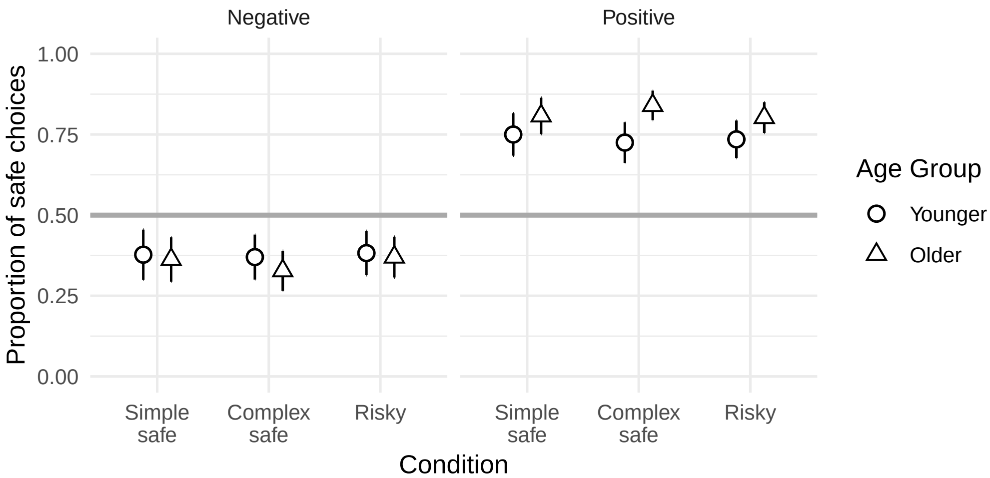

Figure 3.5: Choice proportions of the safe (or low risk) option on the framing task, for problems presented in negative framing (left panel) and positive framing (right panel). Overall, there was a pronounced framing effect in the expected direction: Participants predominantly chose risky options in the negative frame, and predominantly chose safe options in the positive frame. This pattern emerged in both age groups and was unaffected by manipulating the complexity of safe options. Error bars indicate 95 % confidence intervals.

We tested the hypothesis that the magnitude of the framing effect might decrease when safe options are displayed in a more complex format. To this end, we calculated Bayesian logistic GLMERs with the choice of the safe option in the framing task as the outcome variable, and frame, condition, and their interaction as fixed predictors. The model also included a random intercept for each participant. This model was calculated separately for each age group. As Table 3.4 shows, the interaction between frame and condition (complex safe) was not credible in either age group. That is, the magnitude of the framing effect did not depend on the complexity manipulation, in either age group. Likewise, there was no credible interaction between frame and condition (risky), indicating that neither younger nor older adults showed a stronger (or attenuated) framing effect when the second option was also risky, compared to when it was safe.

These results indicate that choices in the framing task were not a function of the complexity of safe options. This was the case in both younger and older adults. Hence, the results also speak against a stronger response to option complexity in older adults in this type of choice task.

Table 3.4: coefficients and 95% Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Framing Task, by Age Group

Outcome: Safe choice Predictor	Younger	Older
(Intercept)	**1.47** **[1.06, 1.87]**	**1.7** **[1.35, 2.07]**
Frame (negative)	**-2.11** **[-2.45, -1.75]**	**-2.38** **[-2.74, -2.05]**
Condition (complex safe)	-0.16 [-0.51, 0.19]	0.26 [-0.12, 0.65]
Condition (risky)	-0.1 [-0.45, 0.26]	-0.02 [-0.39, 0.33]
Frame × Condition (complex safe)	0.11 [-0.38, 0.58]	-0.46 [-0.97, 0.04]
Frame × Condition (risky)	0.11 [-0.38, 0.6]	0.05 [-0.4, 0.54]

3.3.3 Intertemporal Choice Task

Next, we turned to analysing choice behavior on the intertemporal choice task. We first analysed data from the attention check trials, where the sooner option also offered the larger reward. As shown in the left panel of Figure 3.6, participants predominantly chose the dominant (larger sooner) option. When the larger sooner option was simple, it was chosen on 98.96% of the trials by younger adults, and on 98.96% of the trials by older adults. When the larger sooner option was presented in a more complex format, making it more difficult to identify that this option was dominant, it was still chosen in 89.17% in younger adults and 83.12% in older adults. In the condition with two delayed options, the larger sooner amount was chosen on 98.54% of the trials by younger adults, and on 98.33% of the trials by older adults. Overall, these high choice proportions of dominating options indicate that participants worked on the task attentively. The lower proportion of choices of the dominant option in the complex safe compared to the simple safe condition indicates that higher complexity affected decision quality negatively. This result is statistically corroborated in analyses presented in Appendix B.3.

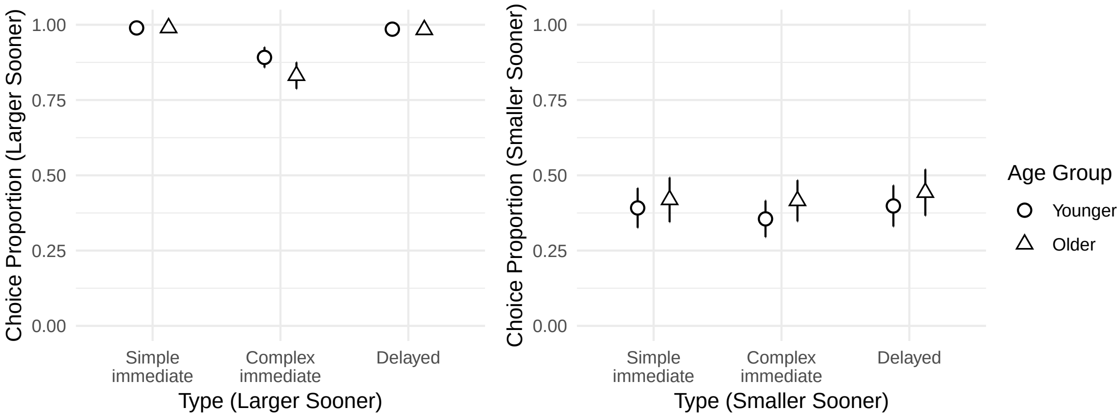

Figure 3.6: Choice proportions in the intertemporal choice task. Left panel: On attention check trials, where the sooner reward was also larger, participants almost always chose this dominant option. Increasing the complexity of the dominant option affected performance negatively, indicating lower decision quality. Nevertheless, the dominant option was still chosen in a great majority of cases. Right panel: In the non-dominated trials participants rather tended to choose the larger later option, and this behavior was unaffected by the complexity manipulation or by age group. Error bars indicate 95 % confidence intervals.

Next, we analysed data on the non-dominated trials, where the sooner reward was smaller than the later reward. Such trials are typically used to measure delay discounting. To test our hypothesis that increasing the complexity of immediate rewards may affect the tendency to choose these immediate rewards, we calculated Bayesian GLMERs with choices of the smaller sooner option as the outcome variable, with fixed predictors for condition and each participant's self-report on patience and impulsivity, as well as a random intercept for each participant. Such a model was calculated separately for each age group. Coefficients and 95% posterior intervals are displayed in Table 3.5. Increasing the complexity of immediate rewards decreased younger adults' tendency to choose these options credibly. Older adults' choices were not credibly affected by increasing the complexity of immediate rewards. That is, our hypothesis that increasing immediate options' complexity may reduce delay discounting is supported in younger adults but not in older adults. These results also indicate that the age groups differed in their response to increasing the complexity of immediate options.

Table 3.5: Coefficients and 95% Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Intertemporal Choice Task, by Age Group

Outcome: Smaller sooner choice 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-report (patience)	-0.02 [-0.2, 0.16]	0.05 [-0.18, 0.3]
Self-report (impulsivity)	**0.3** **[0.07, 0.52]**	0.19 [-0.06, 0.45]

Table 3.6: Coefficients and 95% Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Intertemporal Choice Task

Outcome: Smaller sooner choice Predictor	
(Intercept)	**-1.84** **[-3.23, -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-report (patience)	0 [-0.13, 0.14]
Self-report (impulsivity)	**0.25** **[0.09, 0.42]**
Age group (older) × Condition (complex immediate)	**0.26** **[0.06, 0.47]**
Age group (older) × Condition (delayed)	0.1 [-0.11, 0.3]

To further corroborate this finding, we also calculated a Bayesian GLMER across data from both age groups, again with choices of the smaller sooner option as the outcome variable. The model included the same predictors and in addition the interaction between condition and age group. Coefficients and 95% posterior intervals are displayed in Table 3.6. There was a credible interaction between age group and the condition with complex immediate rewards, indicating that the age groups reacted differently to increasing the complexity of immediate rewards. This is consistent with the different main effects of complexity within the individual age groups.

To summarize, the age groups differed in their response to increasing the complexity of immediate options in the intertemporal choice task. Younger, but not older adults, became less likely to choose immediate options when they were displayed in a more complex format, compared to the standard task. This indicates a stronger preference for simple immediate over complex delayed rewards in younger, not older adults. The direction of this effect is somewhat surprising, given our prior finding that older adults show a stronger preference for simple safe over complex risky options in pure domain risky choice tasks (Zilker et al., 2019, see chapter 2). However, it is consistent with the prior literature on age differences in intertemporal choice, indicating that younger adults are generally more sensitive to immediate rewards than older adults.

3.4 General Discussion

Recent work demonstrated that differences in option complexity between safe and risky options, in a choice paradigm commonly used to measure risk attitude, shape age differences in risky choice behavior (Zilker et al., 2019, see chapter 2). This result was replicated in two independent participant samples. In this paper we examined the extent to which differences between options in complexity might also contribute to (age differences in) loss aversion, framing effects and delay discounting, which are often measured with tasks where options differ in complexity.

In each task, we tested if increasing the complexity of the typically simpler option—and thereby rendering the two options more similar in complexity—affected choice behavior. Contrary to our hypotheses, we found no effect of such a manipulation on the tendency to make disadvantageous safe choices when being offered a mixed gamble (typically interpreted as an indicator of loss aversion), and no effect on the magnitude of framing effects. We also found no evidence for age differences in the response to option complexity in these behaviors. Increasing the complexity of immediate rewards in intertemporal choice made younger but not older adults less likely to choose them. Although this indicates an age difference in the response to complexity, the direction of this effect was not expected. How can these results, which for the most part disconfirm our hypotheses, be interpreted and reconciled with our previous findings?

First, it is important to point out that the hypotheses tested here concern different types of choice behavior than our previous research. While Zilker et al. (2019, see chapter 2) investigated the impact of option complexity in pure domain risky choice, our current experiment posed mixed-domain risky choice problems, and risk free choices with delayed outcomes. Hence, not finding the hypothesized effects of complexity in these types of choice problems is not inconsistent with our previous findings. Moreover, our prior research identified some stimulus characteristics (the availability of loss outcomes and of risky outcomes of zero) under which option complexity seemed to have a lesser impact (cf. study 2 in Zilker et al., 2019, see chapter 2). Such features are also present in some of the choice tasks investigated here, and discussed in more detail below. Moreover, in a recent experiment using eye-tracking, we identified that attentional processes can to some extent explain the impact of option complexity on risky choice (Zilker & Pachur, 2019, see chapter 4). The identified attentional mechanism is only expected to modulate choice behavior under quite specific conditions (details below), which may not have been met in the paradigms investigated here. Hence, this mechanistic perspective may also help explain why our hypotheses were disconfirmed. We discuss these potential reasons why we did not find the hypothesized effects, and also some aspects in which our current and previous results overlap below.

3.4.1 How Particular Types of Outcomes May Counteract the Effects of Complexity

Risky outcomes of zero

In Study 2 of Zilker et al. (2019), we compared the impact of complexity differences in choices between safe and risky options without risky outcomes of zero to choices between safe and risky options where each risky option had one outcome of zero. In choices without zero outcomes, older adults were more likely to choose safe gains than younger adults, and increasing safe options' complexity reduced this age difference. If risky options offered an outcome of zero, neither the main effect of age group nor the interaction with option complexity emerged. Why might this be the case? Notably, a risky option with an outcome of zero—for instance, offering a 70% chance to win \$50 and a 30% chance to win nothing, that is, \$0—can be reduced to a 70% chance to win \$50. Since the zero outcome and its associated probability can be ignored, the risky option in this type of choice problem is similarly complex to a safe option—for instance, offering a 100% chance to win \$40. Consequently, complexity differences between safe and risky options are arguably smaller when the risky option has an outcome of zero, compared to when it has two non-zero outcomes.

This is relevant to interpreting our findings on the framing task—since risky options in framing problems typically offer an outcome of zero—for instance *"with a probability of 80% 900 people will die and with a probability of 20% 0 people will die"*. Thus, complexity differences between the options in the framing task may have been comparably low, even in the baseline condition with simple safe options. This may explain why younger and older adults behaved very similarly in the framing task and why we did not find the predicted interaction between age group and the complexity manipulation.

Outcomes from the domain of losses

In the experiments by Zilker et al. (2019, see chapter 2) and Zilker and Pachur (2019, see chapter 4), option complexity affected choice behavior (and age differences therein) primarily in the gain domain, and substantially less in the loss domain. Notably, in our current study, both the loss aversion task and the framing task involved outcomes from the domain of losses. Consistent with our previous findings in the loss domain, we did not find evidence for the hypothesized effects of option complexity in these tasks. Why might losses affect the impact of option complexity on behavior, and age differences therein?

The availability of losses tends to trigger an increased investment of cognitive resources in choice tasks (e.g., Lejarraga & Hertwig, 2017; Yechiam & Hochman, 2013). Consequently, participants facing losses may engage more deeply with information on the options and try harder to maximize EVs. The overall very high level of maximization performance in the loss aversion task (see Appendix B.2) speaks to this notion. In the framing task, maximization performance cannot be assessed, since the two options on each trial had equal EVs. However, an exploratory analysis of RT data in the framing task (see Appendix B.5) showed that older adults' RTs were generally longer in the negative than in the positive frame, indicating a greater cognitive investment in choices about the explicit possibility of losses. Moreover, in both age groups, increasing the complexity of safe options entailed a stronger increase in RTs in the domain of losses than in the domain of gains. This further suggests that participants were especially motivated to do well on the challenging complex choices when they were framed as losses relative to when they were framed as gains.

In summary, the availability of losses may have motivated participants to carefully scrutinize the options, and thus, to rely less on simplifying processing strategies that they may use in choices about gains. Hence, to the extent that the previously documented effects of option complexity in the domain of gains (Zilker et al., 2019, see chapter 2) are a consequence of simplifying strategies, more in-depth considerations due to possible losses may explain why complexity did not affect choices as expected in our current experiment. We next discuss further evidence that simplifying strategies contribute to the emergence of complexity effects, and how this may inform the interpretation of our results.

3.4.2 Strategic Shortcuts and the Impact of Attention

In a recent eye-tracking study, we showed that attentional biases can be a critical driving force for the effects of option complexity on pure domain risky choice. When options differed in complexity, participants predominantly fixated on simpler options, and to some extent ignored information on the more complex alternatives (Zilker & Pachur, 2019, see chapter 4)—indicating a strategic shortcut to choosing between options that differ in complexity. These attentional biases contributed credibly to choice biases in favor of simple safe gains. However, increasing safe options' complexity attenuated both the attentional biases and therefore also the choice biases in favor these of safe options.

Attentional biases

This insight highlights attentional biases as a possible driver for the effects of option complexity on choice. Conversely, differences in option complexity are not expected to bias choice via this mechanism if participants allocated their attention evenly across the options. This may have been the case in some of the choice tasks investigated here: Before the framing task, participants were explicitly instructed to consider all options very carefully, because individual scenarios were repeated with rather small changes to the options that might easily be overlooked. Such an instruction to process all options carefully was not included in previous studies where complexity did affect behavior (Zilker et al., 2019; Zilker & Pachur, 2019). It is possible that this instruction led participants to intentionally antagonize their intuitive or strategic attentional biases towards simpler options in the framing task, thus counteracting the mechanism that contributed to explaining the impact of complexity in the eye-tracking study. Moreover, in intertemporal choice, the options look superficially quite similar, since they typically consist of one reward and one associated time of delivery. Due to the highly similar visual appearance of these options systematic attentional biases may be less common or less pronounced in intertemporal choice than in risky choice—where safe and risky options look quite strikingly different. Therefore attentional mechanism identified in risky choice may contribute less to the effects of complexity differences in intertemporal choice.

EVs of zero

In the loss aversion task, a different feature of the options may have prevented this attentional mechanism from affecting behavior. In the non-distractor loss aversion trials all safe options and some risky options had an EV of zero. Why would this affect how attention modulates choice? A prominent explanation for why attention can modulate choice posits that the impact of attended value information is amplified during the comparison of options (Smith & Krajbich, 2019). This can be formalized in terms of a gaze-weighted value difference, where each option's EV is multiplied by an attentional weight. Notably, under this model, greater attention towards an option with an EV of zero will barely increase this options' likelihood of being chosen—since multiplying any attentional weight by zero still yields zero. Hence, the same account that explains why attention can biase choices in favor of simple safe options with non-zero EVs (in the eye-tracking study) may also explain why attentional biases to simple safe options might have been largely inconsequential when these simple safe options had an EV of zero (in the loss aversion task).

If options with an EV of zero indeed counteract the hypothesized attentional effects of option complexity, then replacing them by non-zero EVs might allow for these effects to emerge. Hence, to assess the plausibility of this idea, we conducted exploratory analyses of the distractor trials in the loss aversion task, where the safe options' EV was unequal zero (see Appendix B.2). In these trials, manipulating safe options' complexity indeed affected the tendency to choose these safe options, and this effect was more pronounced in older adults. This finding is consistent with the notion that options with an EV of zero may act as a gatekeeper for the attentional effects of option complexity. However, since we did not collect eye-tracking data in the present experiment, and since we did not formulate an a priori hypothesis about different effects of option complexity depending on the availability of EVs of zero, we refrain from strong inferences. Yet, testing these ideas may be an interesting direction for future research.

3.4.3 Overall Task Demands and Difficulty

Another reason why we may not have found evidence for the hypothesized age differences in the response to increasing option complexity may have been the overall quite low difficulty of the tasks. Task difficulty can be assessed by decision quality (i.e., the tendency to choose the option with the higher EV, or even the dominated option) in the loss aversion task (cf. Appendix B.2) and in the dominated trials of the intertemporal choice task. In both cases, participants showed impressively high levels of decision quality, even in the more complex conditions. By comparison to the risky choice problems used in (Zilker et al., 2019, see chapter 2), the loss aversion trials employed here were overall much simpler: All probabilities and decimals were either 1, 0 or .5, and rewards were constituted by single-digit numbers. The intertemporal choice problems generally offer less pieces of numerical information, since each option is fully described by one delay and one reward. In the framing task, decision quality can not be directly evaluated since both options on each trial had equal EVs. However, the availability of zero outcomes, which can effectively be ignored, also suggests a relatively low level of overall difficulty. Why might the overall relatively level of computational demands across all tasks have shaped our findings?

Many studies on comparing younger and older adults indicate that age differences in diverse facets of decision making primarily emerge under high (cognitive) task demands. A meta-analysis on behavioral risky choice tasks concluded that age differences emerged primarily in paradigms with high learning requirements (Mata et al., 2011). Older adults also rely more on simpler heuristic strategies, which discard certain aspects of information (Mata et al., 2007), especially in choice problems with a high number of options (Besedeš et al., 2012a, 2012b). Moreover, a meta-analysis on pre-decisional information search concluded that older adults search for less information before choice, especially if options were characterized by a greater number of cues that needed to be integrated (Mata and Nunes, 2010, see also Frey et al., 2015).

In the light of these findings, it seems plausible that differences in complexity between the options only lead to age differences in choice behavior under a relatively high level of baseline difficulty. Hence, the overall difficulty of the tasks investigated here may have been too low for age differences due to differences in option complexity to materialize. The highly similar behavior of the age groups in the baseline conditions with choices between simple and complex options supports this notion. Consequently, the manipulation of option complexity—meant to control for such age differences—may also not have mattered. The overall high level of maximization performance, even if options were rendered more complex, also speaks to this point.

3.4.4 Implicit Versus Explicit Complexity in Intertemporal Choice

The intertemporal choice task is, to some extent, an odd one out in our study. By contrast to the other tasks, our hypotheses on intertemporal choice were based on the assumption that immediate and delayed options differed in complexity *implicitly*, rather than explicitly. That is, we assumed that although immediate and delayed reward consist of a comparable amount of information (a reward and an associated delivery time), the cognitive operations necessary to evaluate them differ in complexity. This is consistent with formal models of delay discounting, which assume that a reward's utility is transformed (discounted) by a hyperbolic or similar function that takes as inputs the discounting parameter k and the associated delay (cf. Frederick et al., 2002; Grüne-Yanoff, 2015). Computing this function seems more complex than evaluating immediate rewards, which are not assumed to be discounted. However, just because intertemporal choice behavior is (for the most part) appropriately described by a particular mathematical function does not mean that decision makers necessarily compute this function explicitly (Berg & Gigerenzer, 2010). Instead, their behavior may be an emergent property of much simpler processes, which bypass the complex computation entirely. In this case, the assumed complexity differences between immediate and delayed options might vanish. Under this perspective, it is not surprising that option complexity did not seem to matter, and our hypotheses were disconfirmed.

However, one curious finding remains unexplained. Increasing the complexity of immediate rewards made younger, but not older adults, less likely to choose these options. That is, in this paradigm younger rather than older adults appeared to be more sensitive to option complexity, by contrast to our previous finding in risky choice (Zilker et al., 2019, see chapter 2). It is possible that, regardless of the apparent similarity between choices about risks and about delays, fundamentally different (neuro-)cognitive mechanisms may be involved. This might explain why moderators such as option complexity and age also have divergent effects in the different paradigms.

3.4.5 Convergence with Previous Findings

We have discussed many dissimilarities between the findings presented here and those in our other experiments, and also offered some potential explanations how these differences might come about. However, it has to be noted that there are also some close similarities between the current and previous findings on the effects of option complexity.

Decision quality

The first similarity concerns the effect of option complexity on decision quality. Decision quality can be assessed in the loss aversion task and the dominated trials of the intertemporal choice task, where one option was objectively preferable in terms of (expected) value. The complexity manipulation affected decision quality negatively in the loss aversion task (see Appendix B.2) and also in the dominated intertemporal choice trials (see Appendix B.3). In the loss aversion trials in which the safe option had an EV unequal zero, this detrimental effect of option complexity on decision quality was also more pronounced in older adults. This aligns with our previous finding that older adults are more sensitive to option complexity than younger adults in decisions under risk.

Response times

A second close similarity to our previous results is the effect of option complexity on response times (see Appendix B.5). Across all choice tasks, the complexity manipulation entailed longer response times. Moreover, we observed interactions between age group and the complexity manipulation on RTs in all three tasks: Response times increased more in older than in younger adults in response to increasing option complexity. Like the interaction between age group and complexity on decision quality, this interactive effect on RTs further supports the notion that older adults are indeed typically more sensitive to differences in option complexity than younger adults. This greater sensitivity to option complexity can lead to age differences in different dimensions of choice behavior (risk preference, decision quality, RT, eye movements). Hence, although we did not find interactive effects of age group and complexity on the hypothesized dimensions of choice behavior, such interactions were observed in other regards, consistent with prior research. These findings suggest that features of the choice task heavily influence which particular dimensions of behavior are affected by complexity.

Complexity aversion

Also supporting inferences from our previous research, our findings provide further evidence against complexity aversion. Under complexity aversion, increasing the complexity of an option (while leaving the alternative option untouched) should reduce the likelihood of choosing the manipulated option. We previously showed that the opposite is sometimes the case: For instance, increasing the complexity of safe losses can make participants choose them *more* (Zilker et al., 2019, see chapter 2). This directly contradicts complexity aversion. Similarly, in the unequal EV trials of our loss aversion task, increasing the complexity of disadvantageous safe options made participants *more* likely to choose these options. Hence, our results highlight once again that participants are not complexity averse—especially when unattractive options are rendered more complex. Rather, manipulations of complexity seem to affect the evaluation of the options in a more subtle manner, and the behavioral consequences of these modified evaluation processes are not accounted for by complexity aversion.

3.4.6 Conclusion

We presented results that largely disconfirmed our hypotheses regarding the effects of option complexity on measuring loss aversion, framing effects, delay discounting, and age differences therein. Although our specific hypotheses were disconfirmed by experimental data, we still gained interesting insights. We came to a better understanding of the boundary conditions for the effects of option complexity on choice behavior, and for age differences therein. That is, the results map out some limits for generalizing our previous inferences (cf. Zilker et al., 2019, see chapter 2) to different choice domains, and to choice problems with specific types of outcomes. This may help control for option complexity as a potential confound for measurement in future research. Moreover, in the light of prevalent publication bias and the replication crisis in psychology, we are convinced that reporting such results is a step in the right direction—hopefully shifting the focus in the evaluation of scientific work away from positive and novel findings, towards interesting research questions investigated with high methodological standards (cf. Munafò et al., 2017).

3.5 Author Contributions

Conceptualization: V.Z. & T.P.; Experimental Materials & Programming: V.Z.; Data Analysis: V.Z.; Writing—Original Draft: V.Z.; Writing—Reviewing & Editing: V.Z.

3.6 Data and Code Availability

Data and code to implement all analyses is hosted at
https://osf.io/859qm/?view_only=841bcbb4702d4fb398699300e9e4b363.

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Zilker, V., & Pachur, T. (2019). Gaze amplifies value in decisions by younger but not older adults [Manuscript in preparation].

4 | Gaze Amplifies Value in Decisions by Younger but not Older Adults

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Chapter 4 constitutes an earlier (preprint, 30. July 2019) version of a manuscript which was subsequently modified and prepared for peer-review:
Zilker, V. & Pachur, T. (2020). *Gaze amplifies value in decisions by younger but not older adults*
Chapter 4 is hence not identical to the version prepared for peer-review!

Abstract

Selective attention can influence choice by amplifying the impact of fixated information during preference formation. This interaction between gaze and value has been demonstrated across diverse choice domains and a majority of individuals in several studies. However, previous studies on the attentional amplification of value information have been conducted in standard samples of younger adults only. Here we investigate if attention affects preferences in younger and older adults alike. In a risky choice task with options of varying complexity, visual attention of both younger and older adults was systematically biased towards simpler options. However, computational modeling in the attentional drift diffusion framework reveals that greater attention to simpler options only amplified the impact of these options on younger, but not on older adults' choices. This can be explained by an impairment of attentional gains in processing efficiency in older adults. Therefore, attentional biases explain preferences for simpler options in younger but not older adults.

4.1 Introduction

Visual attention plays a critical role for choice behavior. People tend to choose the option that they look at longer (Armel et al., 2008; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Glöckner et al., 2012; Glöckner & Herbold, 2011; Konovalov & Krajbich, 2016; Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011; Shimojo et al., 2003; Stewart et al., 2016), and the option that they look at last (Fiedler & Glöckner, 2012; Konovalov & Krajbich, 2016; Shimojo et al., 2003). Suggesting a causal relation, exogenously manipulating visual attention can shape preferences (Armel et al., 2008; Pärnamets et al., 2015; Shimojo et al., 2003). Visual attention affects choices in diverse task domains (S. M. Smith & Krajbich, 2018, 2019) and in a majority of individuals (Thomas et al., 2019), raising the question: Is the impact of attention on preferences a fundamental, possibly invariant regularity in human cognition?

To investigate the link between attention and choice on a firm formal and theoretical foundation sequential sampling models have proven useful. Prominently, the attentional Drift Diffusion Model (aDDM, Krajbich et al., 2010; Krajbich & Rangel, 2011) posits that selective attention amplifies the impact of currently attended information on choice, allowing the model to explain the previously delineated empirical findings. The aDDM implicitly identifies two key factors contributing to the link between attention and choice—both of which may vary across individuals and choice tasks.

The first factor is that selectively attended information is processed more efficiently than non-attended information. This enhancement of processing efficiency is plausibly implemented by a modulation of neural activity that prioritizes the processing of signals that represent attended information (Boynton, 2009; Brown & Friston, 2013; Feldman & Friston, 2010; Fries et al., 2001; Hillyard & Anllo-Vento, 1998; Hillyard et al., 1998; Kastner et al., 1999; Reynolds & Heeger, 2009; Summerfield & Egner, 2009). The second factor is the magnitude and direction of option-specific attentional biases. Only if one option is predominantly attended to its impact on choice can be amplified more than the impact of the alternative option(s).

Attentional biases depend on features of task materials (cf. Orquin & Loose, 2013; Orquin et al., 2018) but they may also differ across individuals—for instance, between younger and older adults. Moreover, measures of selective neural enhancement and suppression indicate that the prioritized processing of attended information may be impaired in older adults (Gazzaley & D'esposito, 2007; Gazzaley & Nobre, 2012). Do older adults' deficits in implementing selective attentional enhancement entail age differences in the impact of attention on choice? Since previous studies on the impact of attentional enhancement on choice were conducted in standard samples of younger participants, this question has yet been unaddressed.

We investigate differences in the impact of attention on choice between younger and older adults, addressing both factors outlined above, in an eye-tracking experiment on risky choice. We evaluate age differences in option-specific attentional biases using fixation patterns. Using an attentional Wiener drift diffusion model, we investigate if attention enhances the efficiency of processing attended value information to the same degree in younger and older adults, and how this, together with option-specific attentional biases, shapes risky choice in younger and older adults. Since this approach builds on the attentional mechanism described in the aDDM, we first review this model in more detail.

4.1.1 The Link Between Attention and Choice in the aDDM

The aDDM captures empirical findings on the impact of attention on choice, like those outlined in the introductory paragraph, remarkably well (Krajbich et al., 2010; Krajbich & Rangel, 2011). The explanatory mechanism in the aDDM can be summarized as an interaction between gaze and value (S. M. Smith & Krajbich, 2019). Two factors—attentional gains in processing efficiency and option-specific attentional biases—constitute this mechanism. Because we use a risky choice task in our experiment we introduce the model in the exemplary case of choices between safe and risky options.

In the aDDM, preferences are constructed by sequentially sampling noisy evidence on the options' values until the accumulated evidence in favor of one option exceeds the evidence in favor of the alternative by a pre-defined threshold amount. Evidence in favor of the safe option DV_{safe} and evidence in favor of the risky option DV_{risky} are initialized at 0 on time-step $t = 0$. On each subsequent discrete time-step t the values of the safe and the risky option EV_{safe} and EV_{risky}, scaled by the constant $d = 0.01$, with added samples of Gaussian noise $\epsilon \sim \mathcal{N}(0, \sigma^2)$, are sampled as evidence. On each step t either the safe or the risky option is attended to. On time-steps t where the safe option is attended to DV_{safe} and DV_{risky} evolve according to

$$\begin{aligned} DV_{safe}(t) &= DV_{safe}(t-1) + d * \theta_{attended} * EV_{safe} + \epsilon \\ DV_{risky}(t) &= DV_{risky}(t-1) + d * \theta_{unattended} * EV_{risky} + \epsilon \end{aligned} \tag{4.1}$$

and on time-steps t where the risky option is attended to DV_{safe} and DV_{risky} evolve according to

$$\begin{aligned} DV_{safe}(t) &= DV_{safe}(t-1) + d * \theta_{unattended} * EV_{safe} + \epsilon \\ DV_{risky}(t) &= DV_{risky}(t-1) + d * \theta_{attended} * EV_{risky} + \epsilon \end{aligned} \tag{4.2}$$

The aDDM does not predict which option is attended to on a given time step, but uses measured fixation data as input to the model. Once the relative evidence $DV(t) = DV_{safe}(t) - DV_{risky}(t)$ surpasses the positive (negative) choice threshold, indicating that accumulated evidence in favor of the safe (risky) option exceeds the accumulated evidence in favor of the risky (safe) option by a sufficient amount, the safe (risky) option is chosen. Figure 4.1 illustrates exemplary aDDM processes for different parameter settings.

Attentional Gains in Processing Efficiency

The parameters $\theta_{attended}$ and $\theta_{unattended}$ capture that evidence for each option evolves at a faster rate whenever this option is attended to. The evidence for the currently attended option on each step t evolves with $\theta_{attended} = 1$. Evidence for the other (unattended) option on each step t evolves with $\theta_{unattended} \leq 1$. In the most extreme case with $\theta_{unattended} = 0$ evidence for an option does not change at all when it is not attended to (cf. Krajbich & Rangel, 2011).

The discrepancy between $\theta_{attended}$ and $\theta_{unattended}$ captures *attentional gains in processing efficiency*—that is, it captures how strongly selective attention prioritizes the processing of information on the attended option. Under $\theta_{unattended} = \theta_{attended} = 1$ attention does not enhance processing efficiency, and evidence accumulates proportional to the objective value difference between the options (see Panel A and B in Figure 4.1). Under $\theta_{unattended} < \theta_{attended}$ evidence on the attended option's value accumulates at an amplified rate, compared to when it is not attended (see Panel C and D in Figure 4.1). That is, selectively attending to a subset of information (one option) increases the efficiency with which the value signal provided by this information can be processed.

These attentional gains in processing efficiency can increase the impact of the attended option on choice. Hence, the magnitude of attentional gains in processing efficiency is the first key factor shaping the impact of attention on choice in the aDDM. However, the behavioral consequences of these attentional efficiency gains crucially depend on a second factor: The existence, direction, and magnitude of attentional biases.

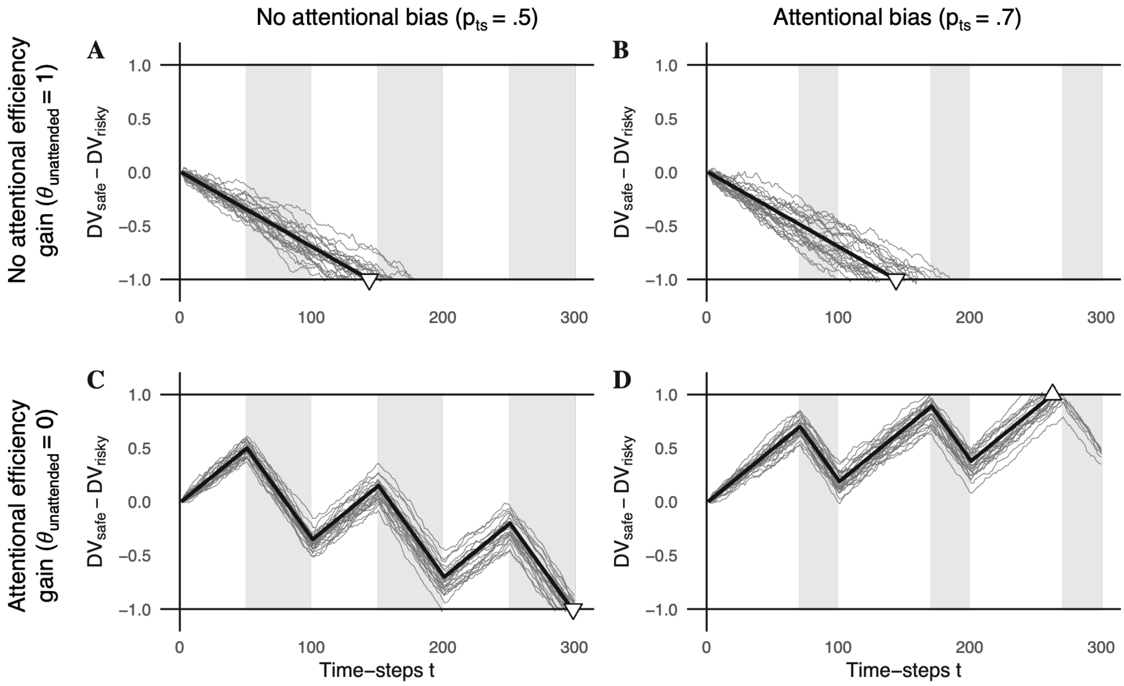

Figure 4.1: How do attentional gains in processing efficieny and of attentional biases affect evidence accumulation in the aDDM? Illustration for an exemplary choice problem, offering a safe option with $EV_{safe} = 1$ and a risky option with $EV_{risky} = 1.7$. The relative evidence in favor of the safe option versus the risky option accumulates over time, and attention alternates between the safe and the risky option (white background: attention to safe option, gray background: attention to risky option). When the accumulated relative evidence exceeds one of the choice thresholds, here set at ± 1, the corresponding option is chosen. The upper threshold corresponds to the safe option, and the lower threshold corresponds to the risky option. The top panels A and B illustrate processes where attention does not enhance processing efficiency ($\theta_{unattended} = 1$), and the bottom panels C and D illustrate processes where attention does enhance processing efficiency ($\theta_{unattended} = 0$). The left panels A and C illustrate processes where attention is distributed evenly across the options (no attentional bias, $p_{t_s} = 0.5$), and the right panels B and D illustrate processes where attention is biased towards the safe option ($p_{t_s} = 0.7$). Each panel depicts several exemplary noisy diffusion processes (gray fuzzy lines), and, for clear illustration, a noise-free process (thick black line). A) In the absence of attentional gains in processing efficiency and of attentional biases, evidence accumulates proportional to the objective value difference $EV_{safe} - EV_{risky}$. Hence the higher-valued risky option is chosen. B) If there are attentional biases to one option, but attention does not enhance processing efficiency, evidence still accumulates proportional to the objective value difference $EV_{safe} - EV_{risky}$. Hence the higher-valued risky option is still chosen. C) If attention enhances processing efficiency, evidence in favor of the currently fixated option accumulates faster. If there are no attentional biases, the attentional advantages of both options cancel each other out. Hence the higher-valued risky option is still chosen. D) If attention enhances processing efficiency *and* if attention is biased towards the lower-valued safe option, evidence in favor of the safe option is amplified for a longer proportion of processing time than evidence in favor of the alternative. Hence attention systematically increases the probability of choosing the lower-valued option, and thus biases choice. In all four cases, noise in the process can induce non-systematic deviations from the predicted behaviors.

Option-Specific Attentional Biases

Either the safe or the risky option is in the focus of attention on each time-step t. The proportion of time spent attending to the safe option p_{t_s} captures the *attentional bias* in the process: p_{t_s} equals 0.5 if both options are attended to for equal amounts of time. There is an attentional bias to the risky option if $p_{t_s} < 0.5$ and an attentional bias to the safe option if $p_{t_s} > 0.5$.

Why do attentional biases crucially shape the impact of attentional gains in processing efficiency on choice? For illustration, consider an aDDM process where selective attention strongly amplifies processing efficiency (e.g. under $\theta_{unattended} = 0$). If attention is allocated evenly across the options—meaning that there are no attentional biases—value information on both options is amplified for 50% of the processing time (see Panel C in Figure 4.1). Hence, the amplifying effects of attention on both options cancel each other out. The model tends to choose the same option that it also chooses when attention does not amplify processing efficiency (cf. Panel A in Figure 4.1)—the higher valued option. That is, in the absence of attentional biases, attentional gains in processing efficiency do not bias choice behavior.

However, if attentional biases exist, attentional gains in processing efficiency can create a systematic advantage for an option, even if this option objectively has a lower value than the alternative: For instance, if attention is allocated to the safe option for 80% of the processing time, the accumulation of evidence in favor of the safe option is amplified for a longer proportion of time, compared to the accumulation of evidence in favor of the risky option (see Panel D in Figure 4.1). Hence, the probability of choosing the safe option increases—even if it is objectively less valuable than the risky option. Therefore, the model can explain why looking longer at an option can increase the probability of choosing it.

Note that due to the noise ϵ in the process, the model does not always choose the option considered preferable under a fully deterministic (undisturbed by noise) computation of evidence, based on the interaction between gaze and value. Instead, on individual trials, the model can show some non-systematic deviations from these behaviors.

To summarize, there are two variables systematically shaping the impact of attention on choice behavior in the aDDM: The magnitude of attentional gains in processing efficiency, and the magnitude and direction of attentional biases. In the absence of option-specific attentional biases, attentional gains in processing efficiency do not affect predicted choice proportions. Vice versa, if attention does not enhance the efficiency of processing attended information, attentional biases do not affect predicted choice proportions. Only if attentional gains in processing efficiency are paired with attentional biases, they systematically bias choice.

4.1.2 Hypotheses on Age Differences in the Impact of Attention on Choice

A currently emerging literature suggests that the impact of attention on choice varies across individuals (S. M. Smith & Krajbich, 2018; Thomas et al., 2019), and that this variability translates into systematic individual differences in choice patterns. For instance, participants who display a stronger link between attention and choice perform worse at choosing the best option in the choice set (Thomas et al., 2019). Here we extend this line of research by investigating systematic differences in the attention-choice link between younger and older adults. Based on the attentional dynamics of preference construction described in the aDDM, we next develop hypotheses on potential age differences in the impact of attention on choice: We flesh out how attentional gains in processing efficiency and option-specific attentional biases may differ between younger and older adults. Our core hypotheses are summarized in Table 4.1.

Age differences in attentional gains in processing efficiency

On a neurocognitive level, the attentional gains in processing efficiency described in the aDDM may be implemented in terms of top-down modulatory control. This mechanism enhances neural activity representing currently relevant information and suppresses irrelevant, distracting information. For instance, top-down modulation implements the attentional selection necessary to restrict capacity-limited working memory contents to task-relevant objects (Gazzaley et al., 2005; Gazzaley & Nobre, 2012). Notably, top-down modulatory control seems to be impaired in older adults. Older adults show reduced neural activity in structures thought to support attentional control, and an stronger neural response to distracting stimuli than younger adults (Chao & Knight, 1997; Gazzaley et al., 2008; Gazzaley et al., 2005; Gazzaley & D'esposito, 2007; Gazzaley & Nobre, 2012; Milham et al., 2002). Moreover, behaviorally, older adults show higher error rates on tasks which require to focus on target stimuli and ignore distracting stimuli (Chao & Knight, 1997; Gazzaley et al., 2005). It seems plausible that mechanisms of prioritized neural processing, like top-down modulation, also implement the attentional gains in processing efficiency described in the aDDM. Thus we hypothesize that attentional gains in processing efficiency, as captured by the aDDM, may also be impaired (i.e., reduced) in older compared to younger adults, and thus affect preferential choice. If this holds, fixating on an option would amplify the impact of that option's value on preference formation less in older compared to younger adults. As a consequence, attention may have a lesser impact on choice behavior in older compared to younger adults, even if both age groups show similar attentional biases.

Table 4.1: Hypotheses on Potential Differences Between Attentional Processes Between Younger and Older Adults

Attentional variable	Prediction
Attentional gains in processing efficiency	
Directed hypothesis	Attention may enhance processing efficiency more in younger than in older adults.
Consequences for choice	Attention shapes preferences more in younger than in older adults (under identical attentional biases).
Attentional biases	
Undirected hypothesis	Attentional biases may differ in magnitude and direction between younger and older adults.
Consequences for choice	Attention shapes preferences more in the age group displaying more extreme attentional biases (under identical gains in processing efficiency).

Age differences in option-specific attentional biases

Moreover, option-specific attentional biases may differ between younger and older adults in magnitude and/or direction. Previous research on age differences in attentional biases during decision making has mainly focused on affective stimuli. Older adults seem to avoid attending to negative stimuli more than younger adults, possibly due to a strategy of emotional regulation that becomes more prominent in older age (L. O. Lee & Knight, 2009; Mather & Carstensen, 2003, 2005). Likewise, in risky choice, older adults may place an increased emphasis on wins and a decreased emphasis on losses compared to younger adults. This is suggested by a model-based analysis of IOWA gambling task data (Wood et al., 2005), and by findings of reduced loss aversion in older adults (Pachur et al., 2017). However, these studies provide no direct measures of visual fixation patterns, and are also uninformative regarding domain-pure risky choice problems. Studies on eye movements in risky choice exist, but are typically conducted in standard samples of younger adults only (cf. Fiedler & Glöckner, 2012; Franco-Watkins & Johnson, 2011; Glöckner et al., 2012; Glöckner & Herbold, 2011; S. M. Smith & Krajbich, 2018; Stewart et al., 2016; Su et al., 2013; Venkatraman et al., 2014).

Therefore, we formulate a non-directed, exploratory hypothesis: Younger and older adults may differ in their option-specific attentional biases. Attention may have a stronger impact on preference in the age group displaying more extreme attentional biases (depending on attentional gains in processing efficiency).

4.2 Outline of the Study

We investigate whether the impact of attention on choice differs between younger and older adults, in terms of two factors, namely attentional biases and attentional gains in processing efficiency. We test these hypotheses in a risky choice experiment using eye-tracking. Risky choice is a domain where preferences have previously been found to be shaped by attention (in standard samples of younger adults, cf. S. M. Smith & Krajbich, 2018), and risky choice behavior often differs between younger and older adults (cf. Best & Charness, 2015; Mather et al., 2012; Pachur et al., 2017). Hence, our experiment implicitly also tests if differences in attentional mechanisms between younger and older adults contribute to age differences in risky choice. To test for age differences in attentional biases we use fixation patterns. To test for the hypothesized age differences in attentional gains in processing efficiency we model choices and RTs in an attentional variant of the Wiener Drift Diffusion Model. This also allows us to capture the combined effects of attentional efficiency gains and attentional biases on preferences in younger and older adults.

Besides investigating age differences in the impact of attention on risky choice, a second aim of this study is to further assess the generalizability of the effects of option complexity on risky choice. Following Zilker et al. (2019, see chapter 2) and Orquin and Loose (2013) we define option complexity as a surface feature of stimulus information, that is, the amount of information used to describe each option in a risky choice task. For instance, the complexity of safe options, which are fully described by a single outcome and the associated probability of 100%, is typically lower than the complexity of risky options with several non-zero probabilistic outcomes, which need to be described by at least two outcomes and the associated probabilities. In two previous studies (Zilker et al., 2019, see chapter 2) we showed that older adults are more likely to choose safe gains over risky gains than younger adults, but only if the safe gains are less complex than the risky ones. That is, the apparently increased certainty effect in older adults—the overweighting of safe outcomes over probabilistic ones (cf. Kahneman & Tversky, 1979; Mather et al., 2012)—to some extent reflects a response to differences in option complexity (Zilker et al., 2019, see chapter 2). Recently, Bernheim and Sprenger (2019) posited that the certainty effect may only be a special case of a more general aversive response to option complexity. Our previous studies do not warrant inferences about this more general claim, since we only manipulated the complexity of safe options in choices between safe and risky options. In our new experiment, we hence manipulate the complexity of high and low risk options, both in choices where safe options are available and in choices between two risky options. This allows us to investigate if option complexity also affects choices where certainty is not a factor.

As a convenient side-effect, manipulating option complexity may help elicit option-specific attentional biases. As outlined above and illustrated in Figure 4.1, attentional gains in processing efficiency (and by extension, age differences therein) only affect choice behavior if participants also show attentional biases. However, based on the previous literature on eye-movements in risky choice it is not clear whether participants—of any age group—show systematic option-specific attentional biases in risky choice, and if so, in which direction. However, a review on eye-movements in decision making concluded that complexity affects fixation durations (cf. Orquin & Loose, 2013). Hence, manipulating the complexity of individual options within risky choice problems may help ensure that attentional biases emerge, at least in some conditions of the task—even though we do not know if attention is biased in baseline risky choice problems where complexity is not intentionally manipulated.

4.3 Methods

4.3.1 Participants

80 younger adults (age in years: range 18 - 35, $M = 25.1$, $SD = 3.82$) and 80 older adults (age in years: range 60 - 78, $M = 69.1$, $SD = 3.59$) participated in the study. Participants were recruited via the internal participant data base of the Max Planck Institute for Human Development Berlin. The participant sample is characterized in more detail in Table 4.2.

Table 4.2: Participant Characteristics. Cognitive and Affective Scales as well as Self-report Measures were Administered After the Risky Choice Task.

	Younger adults			**Older adults**		
	M	*SD*	*Range*	*M*	*SD*	*Range*
Age (years)	25.1	(3.82)	[18; 35]	69.1	(3.59)	[60; 78]
DSST						
— % accurate	0.95	(0.04)	[0.76; 1]	0.98	(0.03)	[0.86; 1]
—n accurate	55.05	(7.82)	[39; 84]	39.33	(5.65)	[29; 57]
WORD score	0.79	(0.11)	[0.06; 0.92]	0.90	(0.04)	[0.78; 1.00]
OS score	0.71	(0.14)	[0.17; 0.99]	0.42	(0.24)	[0.03; 0.91]
Positive affect						
—momentary	3.84	(0.88)	[1.9; 5.7]	4.79	(1.02)	[2.2; 6.9]
—habitual	4.62	(0.83)	[2.4; 6.1]	4.99	(0.83)	[3.6; 6.9]
Negative affect						
—momentary	1.86	(0.78)	[1; 4.2]	1.55	(0.63)	[1; 3.7]
—habitual	2.15	(0.75)	[1; 2.15]	1.68	(0.66)	[1; 1.68]
CRT score	1.19	(1.15)	[0; 3]	0.64	(0.89)	[0; 3]
Numeracy score	3.81	(1.66)	[0; 7]	2.67	(1.57)	[0; 6]
Self-reported risk preference	4.92	(2.24)	[1; 10]	5.03	(1.77)	[0; 9]
Reward (EUR)	-0.22	(2.38)	[-4.45; 4.25]	0.39	(2.48)	[-4.95; 4.35]

4.3.2 Materials

The risky choice task consisted of 108 decision problems, half of which were from the domains of gains and losses. The option space included risky options, offering the chance to obtain one of two non-zero outcomes with probabilities adding up to 100%, and safe options, offering one outcome with certainty (i.e., 100%). Depending on problem type, the more risky option was paired with either a safe option (36 safe vs. risky decision problems), or another less risky option (72 risky vs. risky decision problems). On half of the decision problems the more risky option (in terms of the coefficient of variation $CV = abs(SD/EV)$; Weber et al., 2004)had a higher expected value, and on the other half the less risky option had a higher expected value. The expected value difference between the options ranged between 3 and 20. We ensured that no decision problems included a stochastically dominated option. All outcomes were presented in the experimental currency E$. Analogue to Zilker et al. (2019, cf. chapter 2) the within-subjects manipulation of option complexity was implemented by presenting the options' outcomes in different formats. We implemented options of three different levels of complexity: In a *low complexity* option, each outcome was expressed as a single number, for instance, 60 E$. In a *medium complexity* option, each outcome was expressed as a mathematical term in which an integer (drawn from a uniform distribution between 2 and 120) had to be multiplied by a number between 0.1 and 0.9 (rounded to the second digit). For instance, an outcome magnitude of 60 E$ could be expressed as (0.8 x 75) E$. In a *high complexity* option, the mathematical term expressing the outcome required solving two such multiplications and adding up the results. For instance, 60 E$ could be expressed as (0.2 x 100) + (0.8 x 50) E$. Both in problems involving choices between safe and risky options, and in problems involving choices between two risky options, we manipulated the complexity of the high and the low risk option orthogonally. This results in a 3×3 manipulation of complexity. The different types of options and permuted experimental factors underlying the experimental conditions are illustrated in Figure 4.2. The study was approved by the IRB of the Max Planck Institute for Human Development Berlin.

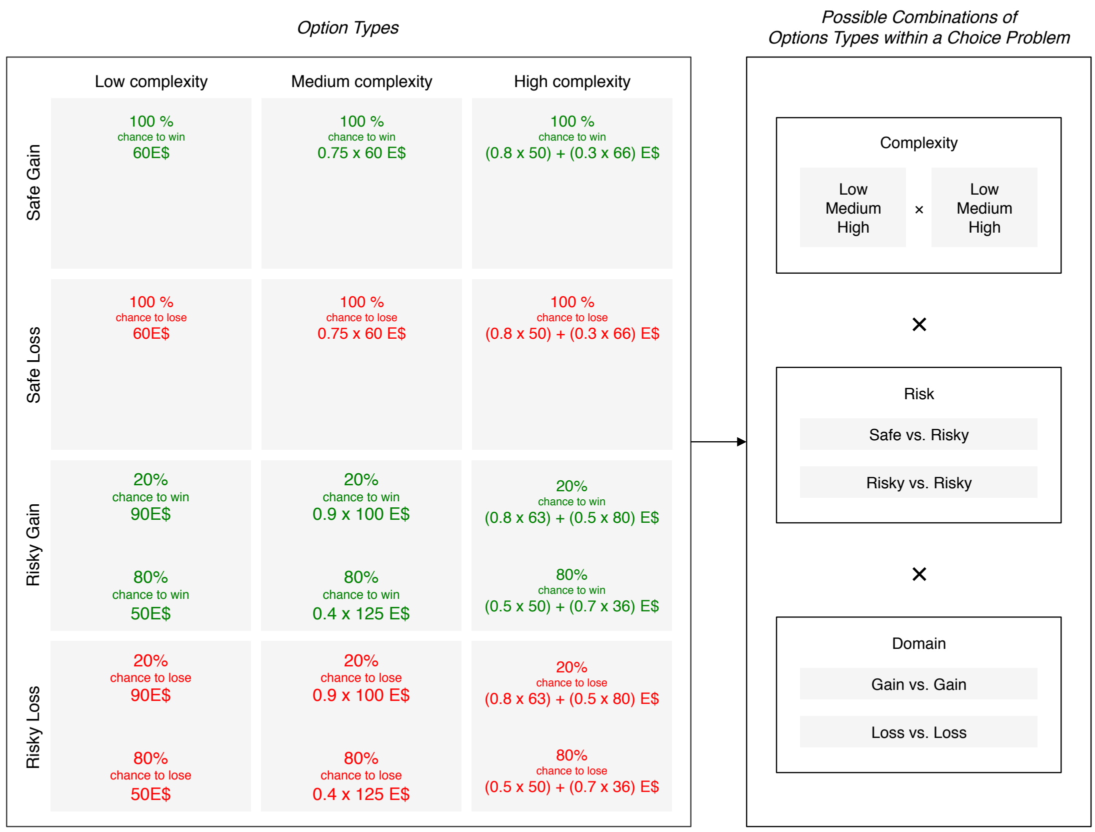

Figure 4.2: Different types of options offered in the risky choice task, and possible combinations of option types within each choice problem. Our design offered safe and risky options, from the domain of gains and losses, of varying levels of complexity (low/medium/high). On each individual choice problem, participants made choices between two options, which both varied in complexity across trials (3×3 levels). Each choice problem offered either a safe and a risky option, or a choice between two risky options. Both options on each choice problem were from the same domain (gains or losses).

4.3.3 Procedure

Upon arriving at the lab, participants provided informed consent for the study. To minimize distractions, each participant sat in one of two laboratory rooms alone. The experiment consisted of two phases: In the first phase, participants worked on the risky choice task while their eye-movements were recorded. In the second phase (without eye-tracking), participants completed several several cognitive tests and provided self-reports regarding affect, risk preferences, and demographic characteristics. The order or the tasks in phase 2 was randomly determined for each participant. All experimental tasks were programmed in PsychoPy v1.90.2 (Peirce, 2007, 2009).

Technical Setup

We used the eye tracker from The EyeTribe (cf. Dalmaijer, 2014). All task information was presented on a computer screen (1920 × 1080 pixels). Participants were asked to sit with their chin positioned comfortably on a head rest, at approximately 50 cm distance from the screen. The vertical and horizontal distance of outcomes and probabilities of the risky choice task on screen was at least 5 cm, amounting to a minimum distance of 5 degrees in visual angle. Hence at any point in time only one attribute could be fixated in the area of highest visual acuity of the fovea (Wertheim & Dunsky, 1980).

Incentivization

Participants received a baseline payment of €20 for participating in the study, and a performance-contingent bonus of €0-10. Before the risky choice task, the experimenter put €5 on the desk in front of the participant as a baseline bonus. The experimenter explained that the choices in the risky choice phase of the experiment would determine if the participant would get to keep this baseline bonus and possibly earn an additional bonus of up to €5, or if they would have to return a part of or even the entire €5 at the end of the experiment. At the end of the risky choice task, one trial was randomly selected, and the lottery chosen by the participant was played out. The resulting outcome was converted from the experimental currency E$ into €, such that 100 E$ converted to €5. The resulting amount in € was added to/subtracted from the baseline bonus of €5, depending on whether it was a gain or a loss trial. Participants obtained the flat fee of €20 for participation irrespective of the lottery outcome. This procedure for the determination of bonuses was also explained to participants in detail during the written instructions of the risky choice task. The experiment and incentivization scheme did not involve deception of participants.

Risky choice task and eye tracking

Before starting the risky choice task, the experimenter told participants that their eye-movements would be monitored, and asked them to rest their chin comfortably on the head rest. Next, the eye-tracker was calibrated using the calibration tool provided by the manufacturer The EyeTribe. After successful calibration, the experimenter started the experiment. Participants received written instructions about the risky choice task and the incentivization scheme on the screen, completed 5 practice trials, and had the opportunity to ask any further questions about the task. Then the risky choice task started. The trials were presented in randomized order, determined uniquely for each participant. The position of options on screen (left or right) and of individual outcome-probability pairs within options (top or bottom) was also randomized uniquely for each participant. Individual trials were separated by a 1 second period with a fixation cross displayed in the center of the screen. After every 20 trials participants had the opportunity to take a self-paced break. They were instructed to stay seated with their head in the headrest to maintain the eye-tracker calibration during each break. After the last trial participants could take another break, while the experimenter uninstalled the headrest from the desk. Then the second phase of the experiment, including cognitive and affective measures, was started.

Berlin Numeracy Test

As solving the more complex choice problems in our task involved more challenging numerical operations we measured participants' numerical skills, using the 7 item version of the Berlin Numeracy Test (Cokely et al., 2012). An exemplary item of this test is *"Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?"* (correct response: 30). The test is scored based on the number of correct responses.

Cognitive style

We measured cognitive style using the cognitive reflection test (CRT, Frederick, 2005). The CRT consists of 3 items, each of which has an intuitive but false response, and a correct response which requires more reflection. All three items are structured similar to the bat and ball question: *"A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?"*. Here the intuitive (but wrong) response is 10 cents, and the correct response is 5 cents. The test is scored based on the number of correct responses.

Working memory capacity

The operation span (OS) task from the working memory battery by Lewandowsky et al. (2010) was used to measure working memory capacity. On each trial, participants had to quickly alternate between judging the accuracy of arithmetic expressions (e.g., $2+7 = 5$) and memorizing consonants. After each sequence of alternating arithmetic expressions and consonants participants had to recall the consonants from the last sequence in correct order. The procedure is described in more detail in Lewandowsky et al. (2010). The task is scored in terms of proportion of consonants recalled correctly.

Affect

We measured momentary and habitual affect, using a German version of the 10 item positive-and-negative-affect scale (PANAS, Grühn et al., 2010; Watson et al., 1988). On each trial of the PANAS an adjective describing an affective state was presented in the center of the screen and participants were asked to rate how strongly they felt this affect right now (measuring momentary or state affect) or generally (measuring habitual or trait affect). Participants responded on a 7-point scale (see Grühn et al., 2010). There were 2 separate blocks for measuring state and trait affect, both including the same adjectives. The 10 positive and 10 negative adjectives were presented intermixed and randomized within each block. The order or the two blocks and of individual trials within each block was randomly determined for each participant.

Fluid intelligence

To measure fluid intelligence in terms of speed of processing, participants completed the digit symbol substitution test (DSST, cf. McLeod et al., 1982). A table on top of the screen defined a mapping between 9 symbols and the digits 1—9. The mapping was randomly determined for each participant individually. On each trial, one of the 9 symbols was presented in the center of the screen, and participants had to press the associated number key. There was no feedback, and the next symbol appeared as soon as the participant responded. The test lasted 90 seconds and participants were instructed to work as quickly and accurately as possible. Before the test phase participants practiced the task during 2 practice rounds (9 trials each). The DSST is scored in terms of number of correctly matched symbol-number pairs. For completeness we also report the percentage of correct responses in Table 4.2, although this measure does not capture speed of processing.

Crystallized intelligence

We measured crystallized intelligence using a lexical decision task, the spot the word test (cf. Baddeley et al., 1993). On each item, participants saw one word and 4 non-words on the screen in randomized order. Participants had to identify the word and respond by pressing a corresponding digit key (1—5). Participants completed one practice item and the test phase, consisting of 36 items of varying difficulty.

Self-reported risk preference

After completing these psychometric tasks, participants were asked to self-report their risk preference on the one-item general risk question (cf. Dohmen et al., 2011): *How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: "not at all willing to take risks" and the value 10 means: "very willing to take risks".*

Demographic information

Finally, participants were asked whether they wore glasses, contact lenses or no vision aids, entered their age and gender and were given the opportunity to comment on the experiment in open format writing. Then the experimenter revealed the result of the random bonus lottery and paid out the participation fee and the bonus.

4.4 Behavioral Data Analysis and Results

We first tested to which extent the effects of option complexity generalized to the manipulation of risky options, and to choices where no safe option was available, and whether these effects differed between younger and older adults. We estimated Bayesian Mixed Effect regressions with different outcome variables (risky choice behavior, RTs and decision quality), using the rstanarm package for R (Goodrich et al., 2018). All models included fixed effects for option complexity (separate for both options), age group, the interaction between option complexity and age group, the absolute difference in EV between the options, a dummy variable indicating whether the more risky option had a higher EV, and a random intercept for each participant. All models were estimated separately for each domain (gains and losses) and type of choice problem (safe vs. risky and risky vs. risky). We also calculated analogue models for the main effects of complexity on each outcome variable within each age group (including all predictors listed above, except for age group and its interaction with option complexity). The effects of fixed predictors were considered credible if the 95% posterior interval on the coefficient excluded zero. Posterior intervals, sometimes also referred to as credible intervals, cover the central 95% of the posterior distribution of the estimated

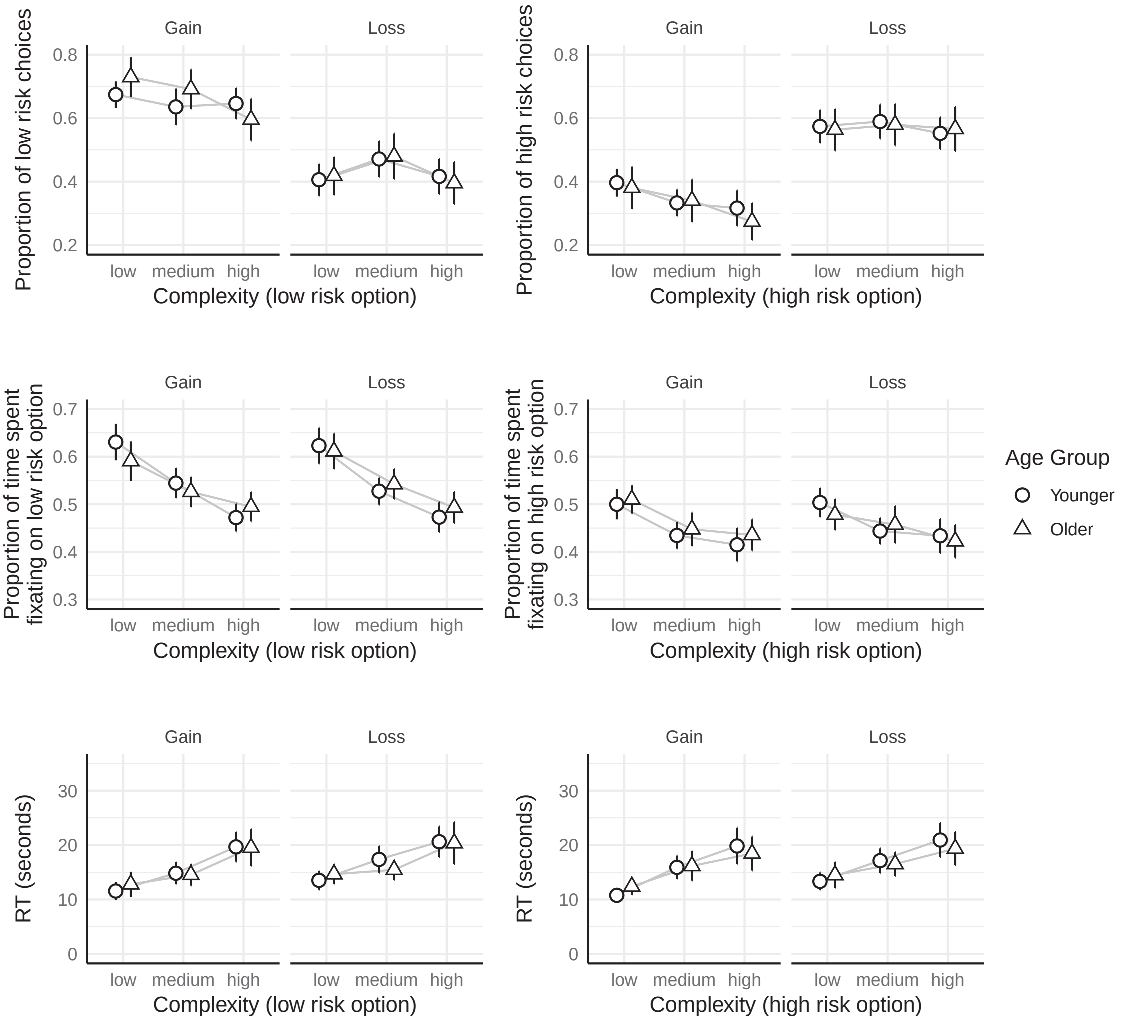

Figure 4.3: Effects of option complexity on risky choice, gaze behavior, and response times, in choices between safe and risky options. Increasing an option's complexity tends to decrease participants' tendency to choose this option, especially in older adults. Increasing an option's complexity also decreases the proportion of time participants spend fixating on this option, and increases RTs. This holds both when increasing the complexity of safe options (left column) and the complexity of risky options (right column). Error bars indicate 95% CI.

coefficients, and can be interpreted as a range which includes the true parameter value with 95% probability (cf. Morey et al., 2016). For each model, we provide a table with all fixed coefficients and the respective 95% posterior intervals. The behavioral results are illustrated in Figure 4.3. Below, we first address the results in choices between safe and risky options and then summarize the key differences in choices between two risky options.

4.4.1 Risky Choice

Increasing the complexity of safe gains decreased participants' tendency to choose these safe gains, and this effect was more pronounced in older adults for highly complex safe gains. Increasing the complexity of safe losses did not affect participants' tendency to choose these options (see top left panel in Figure 4.3). These findings replicate our earlier results on age differences in the response to safe options' complexity on the level of risky choice behavior (Zilker & Pachur, 2019, chapter 2). Moreover, we newly establish that increasing the complexity of risky options has an analogue effect to increasing the complexity of safe options (see top right panel in Figure 4.3): Participants from both age groups chose risky gains less when their complexity increased, and their tendency to choose risky losses was mostly unaffected by the complexity of these risky losses. The GLMER results for risky choice behavior are provided in Table C.1 and C.2.

4.4.2 Response Times

When option complexity increased participants took more time for their choices. These results indicate that participants indeed solved the task in an engaged and motivated manner, even if it was very demanding. This effect emerged when manipulating the complexity of safe and risky options, from both the domain of gains and losses, and in both age groups. Interestingly, younger adults' RTs tended to increase more under higher complexity, compared to those of older adults. The third row in Figure 4.3 illustrates these results. The GLMER results for RTs are provided in Table C.3 and C.4.

4.4.3 Decision Quality

Increasing option complexity also decreased participants' tendency to choose the option with the higher EV, that is, their decision quality. Younger adults showed a more pronounced decrease in decision quality than older adults when the complexity of safe losses increased. The GLMER results for decision quality are provided in Table C.5 and C.6.

4.4.4 Behavioral Results for Choices Between two Risky Options

We also carried out analogue analyses for choices between two risky options, with largely similar results. Increasing the complexity of risky options decreased participants' tendency to choose these options in the domain of gains, but not in the domain of losses. Higher option complexity also increased participants' RTs in both domains, and had a detrimental effect on their decision quality. The GLMER results corroborating all analyses are displayed in Appendix C, and the behavioral patterns are illustrated in Figure C.1.

4.4.5 Summary of the Behavioral Results on Effects of Complexity

The behavioral analyses address our objectives regarding the generalizability of complexity effects in risky choice. We replicate our earlier finding that older adults are more sensitive to the complexity of safe gains than younger adults in terms of risky choice behavior. We further established that not only the complexity of safe options, but also of risky options, affects risky choice behavior, both in choices between safe and risky options, and in choices between two risky options. Therefore, consistent with the argument by Bernheim and Sprenger (2019), the certainty effect may indeed be a specific case of a more general aversive response to option complexity, which affects risky choice behavior in a wider range of scenarios. Moreover, we show that not only older, but also younger adults' risky choice behavior can be shaped by option complexity, especially in choice problems which are highly complex overall (i.e., choice problems involving safe options and highly complex risky options, and choices involving two risky options). In choices between two risky options, the complexity manipulation even affected risky choice behavior more strongly in younger than older adults. In summary, choice behavior displayed by younger and older adults in risky choice problems sometimes used to elicit risk preferences is sensitive to option complexity. The impact of option complexity, a contextual feature which is detached from the options' true risk or value, highlights the constructed nature of these preferences.

4.4.6 Option-Specific Biases in Attention Allocation

Next, we tested our hypothesis about potential age differences in attentional biases using the gaze data. To obtain a measure of option-specific attentional biases we first preprocessed the data as follows.

Preprocessing of gaze data

We identified the fixations in the eye-tracking data using the saccades package for R (von der Malsburg, 2015) and then classified the location of the fixations into areas of interest (AOIs). Each AOI corresponded to one attribute of one of the options (i.e., one outcome or probability). AOIs for outcomes were defined as rectangles of 634 x 183 pixels size (16.1 cm x 4.6 cm on screen) and AOIs for probabilities were defined as rectangles of 317 x 183 pixels size (8 x 4.6 cm on screen), both centered on the location where the attributes were presented.[1] After classifying the fixations into AOIs, we calculated the duration of fixating on each AOI within each trial and subject. To obtain the proportion of time spent fixating on the high and the low risk option in each trial and subject, we summed up the fixation time for the individual AOIs constituting each option, and divided by the total time spent fixating on any AOIs. These option-specific dwell time proportions were used as a measure for option-specific attentional biases for further analyses. For instance, if the proportion of time spent attending to the risky option on a trial is greater than .5, the person showed an attentional bias to the risky option.

Attention allocation

Did manipulating option-complexity indeed help elicit attentional biases, and did such attentional biases differ between younger and older adults? To test this, we estimated Bayesian Mixed Effect regressions, analogue to the models reported for the other dimensions of choice behavior in the previous section, but with the proportion of time spent fixating on the risky option on each trial as the outcome variable.

For choices between safe and risky options, the proportion of time spent fixating on the high risk option is illustrated in the second row in Figure 4.3, and the GLMER results are reported in Table C.7 and C.8. Participants showed pronounced attentional biases towards safe options when they were presented in the least complex format. However, increasing safe options' complexity (and thus rendering them more similarly complex to risky options) reduced or even eliminated these attentional biases: When safe options were highly complex, participants allocated their visual attention more evenly between the options. An analogue pattern also emerges when the complexity of risky options was manipulated. Specifically, when risky options in choices between safe and risky options were presented in a more complex format, participants spent a lower proportion of time fixating on the risky options. This is true for both gains and losses, and crucially, in both age groups. That is, younger and older adults showed very similar option-specific attentional biases towards simpler safe options, and these biases were also similarly sensitive to option complexity in both age groups.

For choices between two risky options, the option-specific dwell time proportions are illustrated in Figure C.1, and GLMER results are displayed in Appendix C.5. By contrast to choices between safe and risky options, participants tended to distribute their attention evenly across the

[1] The width of the probability-AOIs was defined as half the width of the outcome-AOIs, reflecting that probability information took up less horizontal space on the screen than outcome information, as illustrated in Figure 4.2. The height of the AOIs of 4.6 cm on a screen at 50 cm distance corresponds to 5 degrees in visual angle. Hence, when fixating on an attribute, only the contents of the fixated AOI could be fixated within the area of highest visual acuity in the fovea (Wertheim & Dunsky, 1980)

options, irrespective of their complexity, in choices between two risky options. Again, younger and older adults showed highly similar fixation patterns.

4.4.7 Summary of the Behavioral Results on Attentional Biases

Therefore, our non-directed, exploratory hypothesis about potential age differences in attentional biases can be rejected: Younger and older adults showed highly similar attentional biases. While not depending on age, attentional biases strongly depended on stimulus characteristics. Specifically, participants showed pronounced attentional biases towards simple safe options, especially in choice problems with very simple safe options and highly complex risky options (that is, in choice problems where the options differed most strongly in complexity). In choices between two risky options, such systematic attentional biases did not emerge.

4.5 Computational Modeling

Our second hypothesis, regarding age differences in attentional gains in processing efficiency, can not be evaluated based on choice behavior alone. We draw on the attentional drift diffusion framework, which belongs to the class of sequential sampling models (Krajbich et al., 2012; Krajbich & Rangel, 2011; Ratcliff, 1978; Ratcliff & Smith, 2004), to measure age differences in attentional gains in processing efficiency.

The aDDM in its original random walk formulation (as described in the introduction, see Equation 4.1 and 4.2) is difficult to estimate, since it assumes discrete time-steps. Hence, we adapt the Wiener Drift Diffusion Model (Ratcliff, 1978) to implement the core ideas underlying the aDDM. This model can be fitted relatively easily in the hierarchical Bayesian framework, using the Wiener module for JAGS (Wabersich & Vandekerckhove, 2014a). Other authors have resolved the estimation difficulties associated with the aDDM via similar adaptations (Thomas et al., 2019).

Remember that attentional biases are one key prerequisite for attention to affect choice according to the aDDM framework. Since the most pronounced attentional biases were observed in choices between safe and risky options, attention likely affects choice most profoundly in these choice problems. This makes choices between safe and risky options the most interesting application for computational modeling. Hence, when describing the model and the results below, we focus on this problem type. Finally, we also summarize how the results in choices between two risky options differ from those between safe and risky options.

4.5.1 Estimation Strategy

The model was estimated in the Bayesian framework using JAGS. In the Bayesian approach, parameters are estimated by first specifying prior distributions representing initial beliefs about plausible parameter values, and then continually updating them in the light of the data, to obtain posterior parameter distributions. The posteriors estimates represent informed beliefs that incorporate evidence provided by data (cf. M. D. Lee, 2011; Lewandowsky & Farrell, 2018), and they are used for parameter inference—that is, to test whether specific model parameters differ between age groups or conditions (details below). The model was estimated separately for data from each domain and problem type.

4.5.2 Removal of Slow RTs

For computational modeling RTs below 100ms were removed from the data.[2] In total (across all participants and trials) responses on 15 trials in the domain of gains, and 7 trials in the domain of losses were faster than 100ms and thus removed.

4.5.3 Hierarchical Model Structure

The model assumes a hierarchical parameter structure, where parameter values for each individual are informed by a group-level distribution. To capture the hypothesized age differences in the attentional process, we specified separate group-level distributions for younger and older adults. Details on variability in parameters across trials within individuals are provided below.

4.5.4 Distribution of Choices and RTs

In the attentional variant of the Wiener DDM the RT distributions for the two possible responses follow a Wiener process

$$\binom{choice}{RT} \sim \text{Wiener}(\alpha, \delta, \tau, \gamma) \tag{4.3}$$

with the diffusion parameters δ, α, τ, and γ.[3] The Wiener process specifies how evidence accumulates on each trial until a response threshold, corresponding to one of the options, is exceeded and a choice is made. The upper and lower threshold are defined as choices of the safe option and the risky option, respectively. The drift rate δ is the core parameter of interest for our purposes, since it captures the speed of evidence accumulation and how it is modulated by attention, in analogy to the aDDM. Details on the other diffusion parameters are provided in Appendix C.6.

4.5.5 Drift Rate

The drift rate parameter $\delta_{total,i,j}$ captures the speed of accumulation of evidence in favor of the safe option over the risky option, on each trial i in each subject j. A positive drift rate indicates that evidence in favor of the safe option exceeds evidence in favor of the risky option, and vice versa. A drift rate of zero indicates indifference. In order to incorporate the aDDM's core assumption that gaze amplifies the impact of attended value information on evidence accumulation, we defined the parameter $\delta_{total,i,j}$ as a linear combination of subject-level coefficients β_j and trial-level regressors $X_{i,j}$:

$$\begin{aligned}
\delta_{total,i,j} =& \delta_{baseline,j} + \delta_{attention,i,j} \\
=& \delta_{baseline,j} + \underbrace{\beta_{gaze:EV,j}}_{\substack{Efficiency \\ Gain}} * \underbrace{(X_{gaze_{safe}*EV_{safe},i,j} - X_{gaze_{risky}*EV_{risky},i,j})}_{\substack{Gaze-weighted \\ Value\ Difference}}
\end{aligned} \tag{4.4}$$

[2]Removing very fast outliers was necessary because these outliers make it difficult to estimate the non-decision time parameter. Given very few very fast outliers the subject-level non-decision time parameter tends to approach values higher than the fastest outliers. Since such values are logically impossible (the non-decision time can not be longer than the fastest choices), their emergence forcefully terminates MCMC sampling. Removing RTs faster than 100ms was a simple and effective way counteract this issue. It allowed to achieve stable estimation while only requiring to remove very few data points.

[3]We refer to the bias parameter as γ instead of the conventional notation β. We adopt this notation to avoid confusion, as we refer to coefficients on the drift rate as β (details below).

We thereby disentangle the baseline drift $\delta_{baseline,j}$ from the attentional drift $\delta_{attention,i,j}$, which consists of attentional gains in processing efficiency and option-specific attentional biases.

Baseline drift

The baseline drift $\delta_{baseline,j}$ captures systematic aspects of preference formation that do not depend on option-specific attention. This coefficient captures whether participants have a baseline preference in favor of the safe or the risky option, which is not a consequence of the attentional mechanism. We assume that higher complexity may make options appear generally less attractive, even beyond the potential impact of attention. Hence, to capture that increasing an option's complexity may slow down the basline drift in favor of this option, we estimate $\delta_{baseline,j}$ conditional on the level of option complexity.

Attentional drift

The attentional drift $\delta_{attention,i,j}$ captures the systematic impact of attention on preferences: It allows the model to implement the attentional mechanism proposed by the aDDM. It captures how attentional gains in processing efficiency and option-specific attentional biases affect preferences.

Impact of attentional gains in processing efficiency The coefficient $\beta_{gaze:EV,j}$ captures the magnitude of attentional gains in processing efficiency. As previously delineated, selective attention may increase the efficiency of processing attended value information, and thus prioritize and amplify its impact on choice. If the coefficient $\beta_{gaze:EV,j}$ is credibly greater than zero, attending to an option for a greater proportion of time amplifies the impact of this option on preferences. That is, $\beta_{gaze:EV,j}$ mimics the role of the parameters $\theta_{attended}$ and $\theta_{unattended}$ in the random walk formulation of the aDDM (see Equation 4.1 and 4.2).

According to our hypothesis, attentional gains in processing efficiency may be impaired in older compared to younger adults. To evaluate this hypothesis, we test whether $\beta_{gaze:EV,j}$ is lower in older adults than in younger adults.

Besides these potential age differences, it is possible that $\beta_{gaze:EV,j}$ may vary across different levels of option complexity: Selectively attending to an option may increase processing efficiency for value information that is expressed in a simple, easily accessible manner. However, when a more complex description makes value information more difficult to access, this attentional gain in processing efficiency may be dampened. To capture that increasing option complexity may reduce attentional gains in processing efficiency, we estimate the coefficient $\beta_{gaze:EV,j}$ conditional on the level of option complexity.

Impact of option-specific attentional biases Besides attentional gains in processing efficiency, the direction and magnitude of attentional biases contributes to the attentional drift, via the regressor term $X_{gaze_{safe}*EV_{safe},i,j} - X_{gaze_{risky}*EV_{risky},i,j}$. This term captures the difference between the safe and risky option's EVs, weighted by the proportion of time participant j spent attending to each option on trial i. Whereas EVs were experimentally controlled for, attentional biases are under the control of the participants.

Since participants' attentional biases varied across different levels of option complexity, we strongly expect that the attentional drift, which depends on these attentional biases, also varies with option complexity—even if attentional gains in processing efficiency are stable across different levels of option complexity.[4] Therefore, it is essential that our modeling approach allows us to separate changes in processing efficiency $\beta_{gaze:EV,j}$ from changes in attentional biases themselves.

4.5.6 Posterior Predictive Choice Behavior and RTs

Before conducting parameter inference, we inspected whether the model can reproduce key aspects of choice behavior, using posterior predictive choice probabilities and RTs. We simulated behavior based on the subject level posterior mean estimates for all parameters and the original experimental task materials and fixation patterns, by applying the rwiener function from the RWiener package (Wabersich & Vandekerckhove, 2014b). Inspecting posterior predictives can be viewed as a Bayesian analogue to frequentist measures of model fit, and allows to assess if the model successfully accounts for behavior. The simulated posterior predictive behavior is displayed in Figure 4.4. Comparing the posterior predictive choice behavior to the original data (Figure 4.3) shows that the model reproduced the key behavioral regularities well. That is, options were chosen less when they became more complex and RTs increased with complexity. The model also reproduces the interaction between safe options' complexity and age group in the domain of gains.

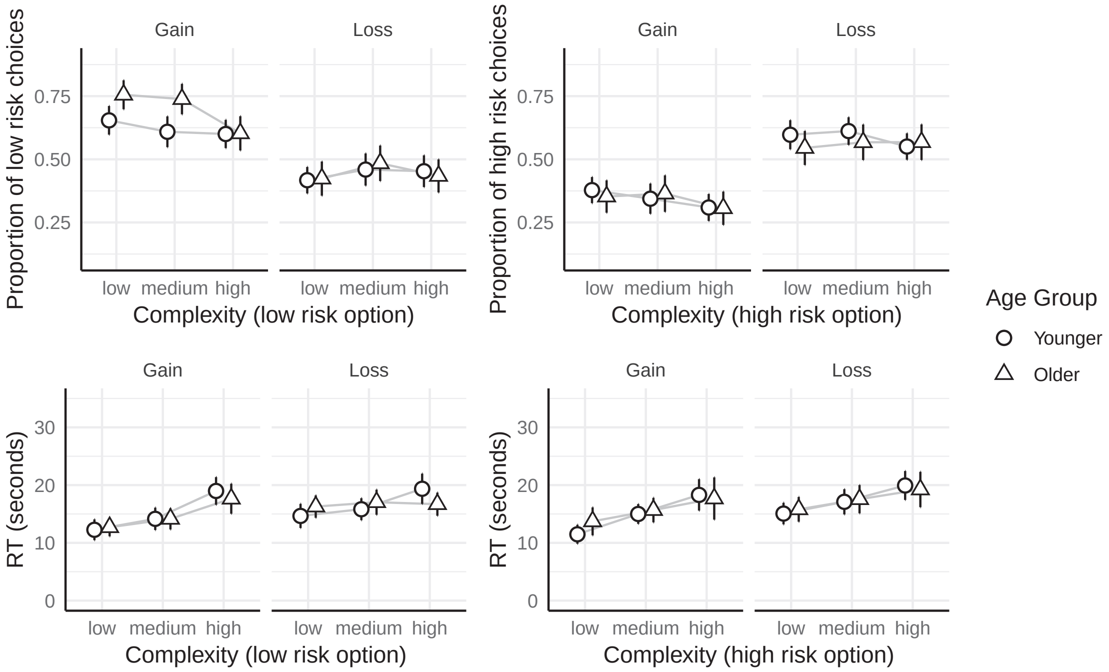

Figure 4.4: The posterior predictive choice probabilities and RTs for choices between safe and risky options reproduce the empirical patterns (cf. Figure 2) very well. Error bars indicate 95% CIs.

4.5.7 Parameter Inference on Attentional Effects in Preference Construction

Attentional gains in processing efficiency

Next we tested our hypothesis that attentional gains in processing efficiency $\beta_{gaze:EV,j}$ may be higher in younger than in older adults. The parameter estimates for $\beta_{gaze:EV,j}$ in choices between

[4]Conversely, even if there were strong differences in processing efficiency gains $\beta_{gaze:EV,j}$ across the different levels of complexity, but no systematic attentional biases, the attentional mechanism would not effectively bias preferences. As illustrated in Figure 4.1 the attentional mechanism only biases choice if attention is biased towards one option.

safe and risky options are displayed in the top panel of Figure 4.5. We estimated Bayesian GLMs with the subject level posterior mean estimates for $\beta_{gaze:EV,j}$ as the outcome variable and the factor age group as the predictor, using the rstanarm package (Goodrich et al., 2018). These GLMs were estimated for each domain and complexity level. To further test if potential gains in processing efficiency in each age group depended on complexity, we also estimated Bayesian GLMs with the subject level posterior mean estimates for $\beta_{gaze:EV,j}$ as the outcome variable and the factor option complexity as the predictor, within each domain and age group. The GLM coefficients and 95% posterior intervals for choices between safe and risky options are displayed in Table C.9 and Table C.10 under *Attentional Efficiency Gains*.

In both domains, attentional gains in processing efficiency were credibly lower in older than in younger adults when safe options were simple, but not when they were highly complex. The analyses within each age group show how these complexity-dependent age differences come about: In older adults, selective attention did not credibly increase the efficiency of processing attended value information (indicated by $\beta_{gaze:EV,j}$ not being credibly larger than zero), and this was largely unaffected by safe options' complexity. In younger adults, attention credibly enhanced processing efficiency when safe options were simple (indicated by $\beta_{gaze:EV,j}$ being credibly larger than zero), but these attentional efficiency gains were credibly reduced when safe options were more complex, at least in the domain of gains.

To summarize, gaze amplified the processing of value information in younger but not older adults' decisions. Moreover, in younger adults, gaze tended to amplify value less under higher option complexity. Therefore, our hypothesis that attention enhances processing efficiency less in older than in younger adults is supported in choices involving simple safe options but not in choices involving more complex safe options—where younger adults' attentional gains in processing efficiency also decrease.

Attentional drift

As outlined earlier, attentional gains in processing efficiency alone do not shape preferences—their impact on choice also depends on attentional biases. Hence, we next test how both aspects in combination contributed to preferences, based on the attentional drift $\delta_{attention,i,j}$. The blue portions of the stacked barplots in Figure 4.5 illustrate the attentional drift in both younger and older adults' choices, separately for the different levels of complexity of the safe options.

To test for age differences in the overall impact of attention on preferences we estimated Bayesian GLMs with the subject level posterior mean estimates for the attentional drift $\delta_{attention,i,j}$ as the outcome variable and the factor age group as the predictor, within each domain and complexity level. We also tested whether the impact of attention on preferences depended on option complexity within each age group, by estimating Bayesian GLMs with the subject level posterior mean estimates for $\delta_{attention,i,j}$ as the outcome variable, and the levels of option complexity as predictors. The GLM coefficients and 95% posterior intervals for choices between safe and risky options are displayed in Table C.9 and Table C.10 under *Attentional Drift*.

Attention had a stronger impact on preferences in younger than in older adults in problems with simple safe options. More precisely, in the domain of gains, the attentional drift in younger adults was credibly greater than zero, and there was a credible negative main effect of age group (older adults). In the domain of losses, the attentional drift in younger adults is credibly lower than zero, and there is a credibly positive main effect of age group (older adults). That is, attention contributed to younger adults' preferences in favor of simple safe gains, and against simple safe losses. Both of these effects were less pronounced in older adults (whose attentional drift was

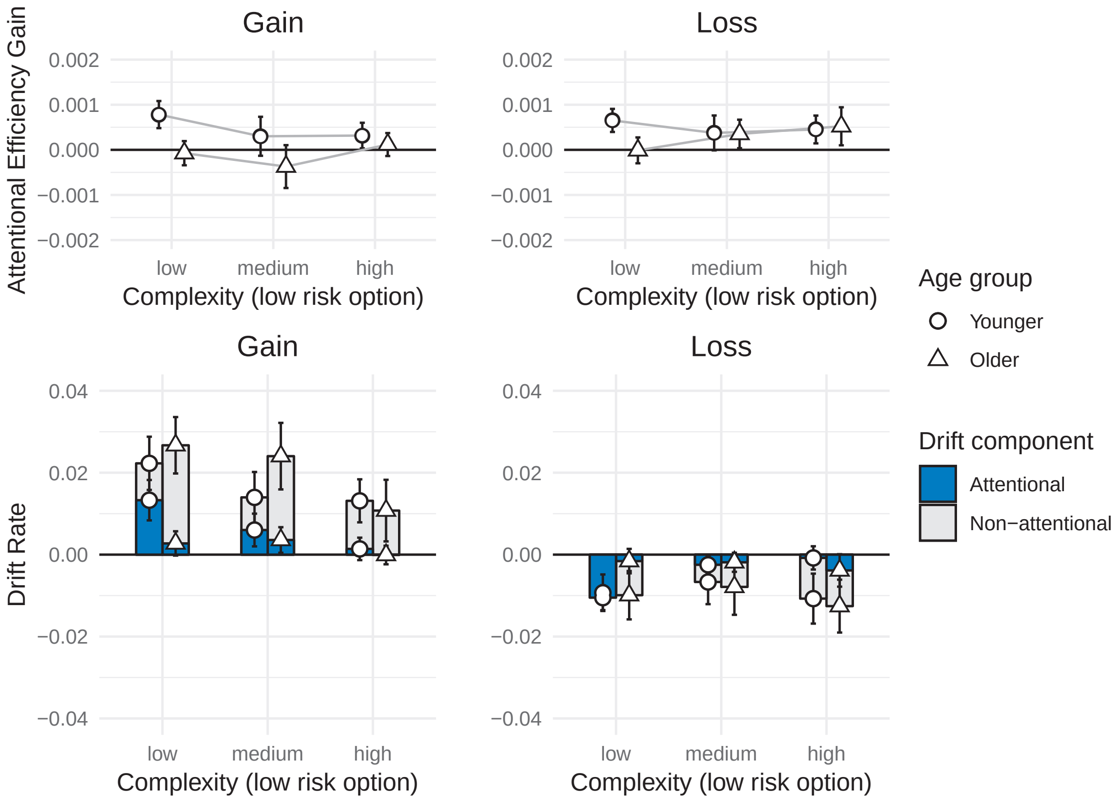

Figure 4.5: Parameter estimates from the attentional Wiener drift diffusion model in choices between safe and risky options, conditional on the complexity of safe options. Error bars indicate 95% posterior intervals. Top panel: Estimates for attentional gains in processing efficiency $\beta_{gaze:EV,j}$. Bottom Panel: Estimates for the drift rate. The total height of the stacked bars represents the overall drift. A positive overall drift rate indicates a preference for safe options and a negative overall drift rate indicates a preference for risky options. The overall drift consists of the attentional drift $\delta_{attention}$ (displayed in blue) and the non-attentional baseline drift $\delta_{baseline}$ (displayed in grey). The relative impact of these components on the overall drift—that is, on overall risk preferences—is represented by the color-coded proportion of the bars.

closer to zero in both cases). This reflects that in choice problems with simple safe gains, both age groups primarily attended to safe options, but only younger adults showed credible attentional gains in processing efficiency: Younger adults' highly efficient processing of the primarily attended safe options amplified the positive evidence in favor of safe gains, and the negative evidence against safe losses. By comparison, older adults showed reduced attentional gains in processing efficiency, such that attention only very weakly contributed to their preferences, even though they also showed systematic attentional biases.

In choices with more complex safe options, where attentional biases were reduced, and where attentional gains in processing efficiency were also less pronounced in younger adults, attention also impacted preferences less (or not at all) in younger adults: When safe options became more complex, the attentional drift towards (/away from) safe options in the domain of gains (/losses) was slower.

Attentional effects in choices between two risky options

Next we briefly summarize the computational modeling results in choices between two risky options. The GLM coefficients and 95% posterior intervals are displayed in Table C.11 and C.12. As in choices between safe and risky options, older adults did not show credible attentional gains in processing efficiency, but younger adults did (at least in choices involving simple options in the domain of gains). In these respects, the results reproduce the patterns from choices between safe and risky options.

However, there is an important difference. Since there were no systematic option-specific attentional biases in choices between two risky options, attention barely biased overall preferences—even in younger adults who showed credible attentional gains in processing efficiency. This is because in the absence of attentional biases, attention amplifies the impact of value information on both options to the same degree, such that their relative advantages cancel each other out.

4.5.8 Parameter Inference on Non-attentional Effects in Preference Construction

We have shown that attention credibly shapes younger adults' preferences in choices between simple safe and risky options. Attention contributed less to younger adults' preferences under higher levels of complexity. This explains, to some extent, why option complexity affected choice behavior in younger adults. However, strikingly, attention did not contribute to explaining older adults' preferences, or why they were sensitive to complexity. Attention also did not explain why preferences depended on option complexity in choices between two risky options, in either age group. That is, risk preferences and their sensitivity to option complexity could not be fully explained by attention.

Systematic effects of complexity on risk preferences, which are not a consequence of attention, are captured in the baseline drift rate $\delta_{baseline,j}$. To investigate how option complexity affected baseline preferences in favor of safe or risky options, we estimated Bayesian GLMs with the subject level posterior mean estimates for $\delta_{baseline,j}$ as the outcome variable and the levels of option complexity as predictors, within each age group, domain and trial type. To assess age differences in baseline preferences we also estimated Bayesian GLMs with the factor age group as the predictor, within each level of complexity, domain, and trial type. The GLM results are displayed under *Baseline Drift* in Table C.10 for choices between safe and risky options and in Table C.12 for choices between two risky options. The grey portions of the stacked barplots in Figure 4.5 illustrate the baseline drift in both younger and older adults' choices between safe and risky options, conditional on the complexity of safe options.

In choices between safe and risky gains both younger and older adults showed credible baseline preferences in favor of safe options, indicated by a positive baseline drift. This effect was more pronounced in older adults. Also, only in older adults this baseline drift in favor of safe options was credibly reduced when the complexity of safe gains increased to a high level. That is, increasing the complexity of safe options made them less attractive to older adults, but not to younger adults. These effects of complexity on the level of baseline drift explain why the tendency to choose safe gains decreased more strongly in older than in younger adults, when these safe gains became highly complex.

How can these changes in older adults' baseline preferences under higher complexity be interpreted? Remember that selective attention did not enhance older adults' processing efficiency of value information, indicating that older adults may have had considerable difficulties with extracting meaningful information on the options' true values. As a consequence, older adults may have relied mostly on surface features of the options (i.e., their complexity) rather than their content (i.e., value information) when making their choices. That is, older adults may have chosen simple safe gains more because they seemed superficially more attractive to them, whereas younger adults chose simple safe gains more because selective attention allowed them to process these options very efficiently, and thus increased the impact of these options on their preferences.

In the domain of losses, younger and older adults showed neutral or negative baseline drift rates, indicating a baseline preference for risky losses over safe losses, or indifference. By contrast to the domain of gains, older adults' baseline drift rate in favor of risky losses was unaffected by complexity. This explains, so some extent, why the age groups responded more similarly to the complexity manipulation in the domain of losses than in the domain of gains on the level of choice behavior. In choices between two risky options, increasing the complexity of low (high) risk options decreased the baseline drift towards these low (high) risk options in the domain of gains, but not in the domain of losses (see Table C.12). These effects emerged in both age groups.

4.6 General Discussion

The link between visual attention and choice behavior has been intensely studied in recent years. Intriguing phenomena, such as the finding that manipulating attention can bias choice (Armel et al., 2008; Ghaffari & Fiedler, 2018; Pachur et al., 2018; Pärnamets et al., 2015; Shimojo et al., 2003), and research suggesting that attention is linked to choice across a wide variety of choice domains (S. M. Smith & Krajbich, 2018) and in a great majority individuals (Thomas et al., 2019) contribute to the widespread fascination with this topic. Yet, existing research has focused on younger adults, leaving the question unanswered if and how attention affects older adults' preferences. Evidence that older adults show deficits in implementing selective attention outside of the preferential domain, for instance in working memory tasks, (e.g., Gazzaley et al., 2008) suggests that this question may be an interesting one to tackle.

We investigated the interplay between age, attention, and preferential decision making in a risky choice paradigm. In this paradigm we manipulated the complexity of safe and risky options to assess the generalizability of our previous findings on the impact of safe options' complexity on risky choice, and age differences therein. These effects largely generalized to the manipulation of risky options' complexity, and to choices between two risky options. Moreover, consistent with previous studies, we showed that attention can profoundly shape choice behavior in younger adults, by contributing to their apparent risk aversion (seeking) in the domain of gains (losses). However, this effect did not generalize to older adults. In older adults, attention did not enhance the efficiency of processing attended value information, and thus did not explain their choices. Moreover, in younger adults, attention only shaped preferences in types of choice problems where attentional biases emerge (in choices between safe and risky options, but not choices between two risky options), and when information on the options was displayed in a comparably simple format. Below, we embed these newly identified boundary conditions for the link between attention and choice in the existing literature and discuss several theoretical and methodological implications.

4.6.1 Attentional Capacities and Preferences in Older Age

Older adults' declining fluid cognitive capacities in terms of processing speed, reasoning, and working memory (cf. Salthouse, 2004) are frequently invoked to explain age differences in choice behavior. For instance, they have been linked to age differences in risky choice in paradigms with high learning requirements (Mata et al., 2011) and with high computational demands (Mamerow et al., 2016), and also to older adults' greater reliance on simpler heuristic strategies (Mata et al., 2007), their greater choice inconsistency (Brocas et al., 2019), and their decreased decision quality (Pachur et al., 2017).

Age differences in the impact of attentional capacities on choice, by contrast, have received only little attention. Those who do discuss attentional processes in aging decision makers typically focus on affect, pointing out that older adults appear to focus more on positive rather than negative information, possibly to regulate emotion (Mather & Carstensen, 2005). Going beyond the affective realm, we demonstrate that age differences in attentional processes profoundly contribute to age differences in choice behavior, by showing that in younger adults, attended information is processed in an enhanced and prioritized way. Neuroscientific evidence suggests that processing enhancements due to selective attention seem to be impaired in older adults (Chao & Knight, 1997; Gazzaley et al., 2008; Gazzaley et al., 2005; Gazzaley & D'esposito, 2007; Gazzaley & Nobre, 2012; Milham et al., 2002). Consistently, our computational modeling demonstrates that older adults' selective visual attention did not enhance their processing efficiency for attended information. As a consequence, choice behavior is explained by attention to a lesser degree in older than in younger adults.

This has some interesting consequences. The model-based analyses reveal that qualitatively similar behaviors in younger and older adults, such as the tendency to choose safe gains less when they become more complex, emerge from different mechanistic underpinnings. While younger adults chose simple safe gains because attention amplified their impact on choice, this was not the case in older adults, due to their attentional impairments. Rather, older adults seemed to choose simple safe gains more because more complex options seemed less attractive to them at baseline, without the impact of attention. By extension, increasing the complexity of safe options modulated the attentional component of preferences in younger adults, but the non-attentional baseline preferences in older adults. Hence, although in both age groups the construction of risk preferences is influenced by option complexity, the specific constructive processes differ quite profoundly. When inspecting mere behavior, however, the consequences of these two mechanisms are necessarily intermixed. Therefore, mere choice behavior may create misleading impressions of age differences in risk preferences, without being informative about the different cognitive mechanisms generating these behaviors in younger and older adults. Since different behavioral tasks for measuring risk preferences tap into these different cognitive mechanisms to different degrees, this finding may help explain the low association between different behavioral measures of risk preferences, and also between each of these measures and the dispositional factor of risk attitude (Frey et al., 2017; Pedroni et al., 2017).

4.6.2 Generalizability of Effects of Complexity in Risky Choice

One objective of our experiment was to further assess the generalizability of the effects of option complexity on risky choice in younger and older adults, which we previously demonstrated (Zilker et al., 2019, see chapter 2). We replicated our previous finding of an interaction between safe options' complexity and age group in the domain of gains, and the finding that the effects of complexity are considerably dampened in the domain of losses. We also extend these findings, by showing that choice behavior is affected not only by the complexity of safe options, but also by the complexity of risky options—that is, irrespective of whether a safe option was available or not. Our results also indicate that complexity affects choice behavior in the same direction in both age groups (more complex options tend to be chosen less), but these effects are sometimes more pronounced in older adults. As outlined in the previous paragraph, however, these similar behavioral tendencies in younger and older adults emerge from different mechanistic underpinnings. Hence, in extension of our prior research, we show that age differences in the response to option complexity do not only differ in magnitude, but also in quality.

4.6.3 Does Gaze Shape or Reflect Preferences?

A question that can hardly be left unaddressed here is whether longer gaze to an option merely reflects that a person evaluates this option positively, or whether it indeed causally contributes to preferences. Is looking at options a consequence of liking them, or the cause thereof? The existence and direction of this causal link is a topic of ongoing and vivid debate. The aDDM implicitly takes a stance on this issue, positing that gaze shapes preferences in a particular manner (details discussed below). Since our analyses are based on these assumptions, we will review some key arguments and findings addressing the direction of the causal relation between gaze and preference, focusing on whether or not they are consistent with the aDDM, and hence with our modeling approach.

Evidence on preferences causing gaze patterns: The gaze cascade

A phenomenon known as the *gaze cascade* (Shimojo et al., 2003) invokes a strong intuition that gaze is a consequence of emerging preferences, rather than their cause: Over the time course of preference formation, participants seem to increasingly look at the option that they end up choosing. An intuitive interpretation of this pattern is that participants increasingly look at options *because* a preference for these options develops. A positive feedback loop, where evolving preferences affect attention allocation and thus amplify mere exposure effects has been proposed to explain this finding (Shimojo et al., 2003). However, Mullett and Stewart (2016) showed that the impression of a temporarily evolving gaze bias can emerge in accumulator models such as the aDDM, even when fixations are in fact allocated randomly: The apparent gaze cascade can be explained as an artefact of retrospectively plotting fixation patterns time-locked to the decision. Moreover, remarkably similar gaze patterns also evolve in non-preferential visual decision making tasks, further underlining that it is not necessary to assume that preferences cause the gaze cascade (cf. Glaholt & Reingold, 2009, 2011).

Evidence on gaze patterns causing preferences: Last fixations

The opposite hypothesis on causality posits that fixations drive preferences. Intuitively supporting this notion, the option that is fixated last is typically more likely to be chosen (Ghaffari & Fiedler, 2018; Krajbich et al., 2010; Pärnamets et al., 2015). In an attempt to test this causality Pärnamets et al. (2015) manipulated which option was fixated last, by externally interrupting the search process and prompting a choice in a gaze-contingent manner. Their data indicates that participants were indeed biased towards choosing the externally determined last fixated option. However, Newell and Le Pelley (2018) demonstrate that the effect in Pärnamets et al. (2015) may be exaggerated due to a selective analysis of particular subsets of data. Based on an analysis of complete data, also including trials that would have been excluded by Pärnamets et al. (2015), Newell and Le Pelley (2018) reject last fixations as a causal factor for preferences.

This is consistent with assumptions of the aDDM. Even though in the aDDM surpassing a response threshold typically coincides with a (last) fixation to the chosen option, the model does not predict that interrupting choice processes biases choices towards the last fixated option: When interrupting the sampling process at an arbitrary time point, the relative evidence accumulated until that time does not necessarily favor the currently (and thus last) fixated option. Consistently, Ghaffari and Fiedler (2018) demonstrate experimentally that last fixations are associated more strongly with choice when they occur as a by-product of (self-terminated) preference formation than when experimentally manipulated.

Evidence on gaze patterns causing preferences: Fixation durations

Does this mean that attention does not causally shape preferences? Notably, there is an interesting twist to Newell and Le Pelley's findings (2018). On trials where participants gazed at the non-target option for considerably longer than at the target option, they chose the non-target option in a clear majority of cases. Hence, even though the experiment speaks against a causal impact of last fixations, it leaves open the possibility for (relative) fixation durations exerting causal influence instead. This causality can neither be accepted nor rejected based on Newell and Le Pelley's experiment, since fixation durations were not explicitly manipulated. However, several other studies have explicitly manipulated the relative duration of gaze towards the options, and thus warrant stronger causal inferences (Armel et al., 2008; Bird et al., 2012; Nittono & Wada, 2009; Shimojo et al., 2003). These studies, too, find that relatively longer gaze towards an option—even if externally manipulated—entails a greater probability of choosing it. It can be demonstrated via simulation that this is consistent with the aDDM, which predicts that manipulating relative fixation duration biases preferences towards the option that was fixated for a longer proportion of time.

Taken together, both theoretical and empirical insights speak against a positive feedback loop where fixations are a consequence of evolving preferences. Evidence suggesting that attention shapes preference points towards fixation durations rather than last fixations exerting causal influence, consistent with the aDDM. The aDDM also sufficiently explains prominent empirical phenomena, such as the gaze cascade and choice biases towards options that are looked at longer, speaking towards the appropriateness of its (causal) processing assumptions.

4.6.4 An Attentional Explanation for Domain Differences in Risky Choice

Our results provide a novel attentional explanation for a hallmark finding in risky choice, the reflection effect. This effect describes a mirroring of preference patterns between the domains, meaning that risk aversion in choices about gains is typically accompanied by risk seeking in choices about losses (Kahneman & Tversky, 1979).

This effect also emerges in our experiment, especially in choices between simple safe and risky options. Our results in younger adults suggest a novel attentional explanation for this effect. Younger adults primarily attended to safe options, and attention amplified the impact of these options' values on choice. That is, the prioritized processing of safe options amounted to amplified (positive) evidence in favor of the safe option in the domain of gains, and to amplified (negative) evidence against the safe option in the domain of losses. That is, the same underlying attentional mechanism—highly efficient processing of attended information paired with attentional biases towards simple safe options—entailed opposite behavioral consequences in the two domains, namely apparent risk aversion for gains and apparent risk seeking for losses. If these behavioral patterns were viewed in isolation from the underlying construction process, they might be mistaken to reflect dispositional risk preferences. However, our results illustrate that these patterns may instead emerge from the processing dynamics of aDDM, a computational model that does not assume an underlying disposition towards risk.

To our knowledge, there is currently only one other published study investigating the impact of the attentional mechanism described by the aDDM in choices about items with negative values (and none in the domain of risky choice). Armel et al. (2008) also find that attentional amplification has reversed consequences for appetitive and aversive options, using food items rather than safe and risky prospects. This is consistent with our results, and with the notion that the same general attentional mechanism may apply in both the domain of gains and losses, but with opposite behvioral consequences.

4.6.5 Implications for Stimulus Design

Attention during decision making is often influenced by irrelevant features that are unrelated to the goals of decision makers, such as the salience, color, size or—as our experiment highlights—complexity (Orquin et al., 2018). As a consequence, Orquin et al. (2018) argue that there is no such thing as a neutral presentation format. Our analyses underline that surface features which induce option-specific attentional biases can crucially shape choice. For instance, attention contributes to younger adults' preferences in choices involving safe options, where attentional biases emerge—but not in choices between two risky options, where such biases are absent. Hence, although we appreciate and agree with Orquin et al.'s (2018) general sentiment regarding the difficulty of achieving truly neutral presentation formats, we think that it can be qualified. At least, there are more or less neutral presentation formats, especially in choice tasks with several options: Formats in which one option is visually particularly distinctive—such as safe options among risky alternatives—may be more prone to attentional biases, compared to formats where the options look superficially more alike—such as in choices between two risky options. Choosing a (rather) neutral presentation format in experimental choice paradigms may hence help to prevent confounds due to a differential impact of attention.

4.6.6 Attentional Biases and Rational Search Strategies

So far we have focused on the impact of attention on choice from a descriptive perspective. Next, we turn to a closely related normative question: How should decision makers best allocate their attention to make good choices?

Mere maximization

When decision makers are judged according to the standard of maximizing expected payoffs, this question is simple to answer: Maximization behavior can be implemented in sequential sampling models in terms of a sequential probability ratio test (SPRT, Bogacz et al., 2006). Notably, the aDDM reduces to an SPRT in the absence of attentional biases (Krajbich et al., 2010). Conversely, the introduction of attentional biases negatively affects maximization performance (except if attention is systematically biased towards the option with the higher EV). Hence, allocating attention evenly across the options is advised to implement the optimal maximization policy of SPRT.

Mere maximization under differential efficiency gains

However, the aDDM only reduces to an SPRT in the absence of attentional biases, if attentional gains in processing efficiency are identical for all options considered. Notably, our computational modeling results indicate that attentional gains in processing efficiency can depend on stimulus characteristics, namely complexity, which can differ between the options within a choice problem. This finding is consistent with a model-based re-analysis of several previous data sets by (Thomas et al., 2019): A model accounting for the impact of a gaze bias on choice was more clearly favored over a model that did not account for gaze in simple perceptual choice than in more complex value-based choice.[5] (Newell & Le Pelley, 2018) also concluded that attention and choice seem to

[5] The authors qualify this finding by pointing out that these differences in model performance might be driven by a higher number of trials in perceptual experiments.

be linked more strongly for simple perceptual choices, especially if evidence is weak, compared to more complex moral choices (but see Ghaffari & Fiedler, 2018).

How do normative implications change if attentional gains in processing efficiency differ between options in a choice problem—for instance, if efficiency gains are greater for simpler options? In this case, attending to a simple option will result in a greater information gain compared to attending to a more complex option over the same time period. Hence, allocating attention evenly across the options entails differences in how precisely the options' values can be assessed, and can also generate an advantage for the simpler option to be chosen which is not necessarily justified by its objective value. Attentional biases towards the simpler option may further reinforce this imbalance (since the decision maker obtains even more excess information regarding the simple option), and attentional biases towards the more complex option may attenuate the imbalance. That is, in order to implement a maximization policy similar to SPRT, decision makers may have to compensate for the higher rate of information gain for simple options by attending longer to more complex options.

The double-edged sword of attention

The above discussion highlights a seemingly paradoxical feature of attention: Enhanced processing efficiency due to attention intuitively seems like a desirable feature for decision makers to have, allowing them to gather precise information faster. However, in situations of binary choice, these efficiency gains can jeopardize the goal to identify the best option. If attention happens to be biased to an inferior option, the efficient processing can enhance the impact of this inferior option so much that it is chosen, even though the other option is objectively preferable. Therefore, attentional gains in processing efficiency may interfere with maximization. Yet, they may help satisficers (Simon, 1955)—who aim to find a good enough option rather than the best option in the choice set, and who may find even inferior options good enough—achieve their aspiration levels faster. That is, depending on which standard for performance is applied, attentional biases may be viewed as a rational or an irrational feature of search. This view converges with the notion that attentional selection may not just be a response to a resource constraint, but an appropriate solution to an inference problem, and can thus be normative (Dayan et al., 2000). In a similar vein, selective integration of evidence—a processing strategy considered suboptimal by classical definitions—can protect choices against late neural noise (which occurs after sensory processing stages), and can thus lead to better decisions (Tsetsos et al., 2016). This intriguing tension has been described as *optimal irrationality* (Tsetsos et al., 2016).

At the current point, we do not have a definite solution on how to exploit the interplay between attentional biases and (different standards for) rational choice. However, it seems feasible to identify the boundary conditions under which attentional biases of a given magnitude and direction may help decision makers achieve their goals (whether maximizing or satisficing) via simulation. This seems like a promising direction for future research, with the potential to counteract the powerful intuition that biases in search or reasoning necessarily indicate irrationality.

4.6.7 Conclusion

Several years ago, Henrich et al. (2010a, 2010b) called into question the generalizability of large chunks of psychological research by pointing out the WEIRDness of standard participant samples—samples drawn predominantly from Western, Educated, Industrialized, Rich, and Democratic (WEIRD) populations. Although it might not have made for such a nice acronym, it seems like the authors were missing a letter—Y, for Younger. Not only do samples in top psychology journals consist of 96% subjects from Western industrialized countries, which house only 12% of the world's population (Arnett, 2008; Henrich et al., 2010a)—they are also typically made up of almost entirely younger adults. Research on cognitive aging is segregated into dedicated outlets, as if older adults were not members of the general population whose psychology—one might assume—the discipline is striving to understand. It is not surprising that inferences about basic cognitive processes, such as the role of attention in decision making, do not seamlessly generalize to older adults. Basic cognitive and motivational processes do not only vary around the globe, but also across the lifespan—and in the interest of understanding the *human* mind, not only a thin slice thereof, this factor needs to be accounted for.

4.7 Author Contributions

Conceptualization: V.Z. & T.P.; Experimental Materials & Programming: V.Z.; Data Analysis and Modeling: V.Z.; Writing—Original Draft: V.Z.; Writing—Reviewing & Editing: V.Z. & T.P.

4.8 Data and Code Availability

Data and code to implement all analyses is hosted at
https://osf.io/v6zmg/?view_only=0d5a5b348c694321a3da5e31e31121fb.

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5 | Signatures of Attention in Risky Choice: Linking Cumulative Prospect Theory and attentional Drift Diffusion Models

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Chapter 5 constitutes an earlier (preprint, 30. July 2019) version of a manuscript which was subsequently modified and submitted for peer-review:
Zilker, V. & Pachur, T. (2020). *Nonlinear probability weighting can reflect attentional biases in sequential sampling.*
Chapter 5 is hence not identical to the version submitted for peer-review!

Abstract

Probability weighting is a key construct allowing cumulative prospect theory (CPT) to account for seminal phenomena of risky choice, such as the fourfold pattern. It describes the impact of a risky outcome on a choice in terms of a nonlinear transformation of its objective probability. Recently, the attentional drift diffusion model (aDDM) formalized how attentional biases can shape preference construction in terms of a sequential sampling process. Here we demonstrate that probability weighting in CPT can account for the effects of attentional biases in aDDM. We simulated choices between safe and risky options using the aDDM while systematically varying option-specific attentional biases. The resulting choices were modeled with CPT. Attentional biases to safe and risky options had highly systematic signatures in the different characteristics of CPT's weighting function (curvature, elevation). We further establish that more linear (objective) probability weighting in CPT is associated with longer response times predicted in the aDDM. We also demonstrate empirically that attentional biases entail systematic patterns in probability weighting. Our findings highlight that apparent distortions in probability weighting may be due to simple option-specific biases in information search, for instance during the sequential sampling of outcomes. These results challenge conventional psychological interpretations of CPT's weighting function. They also suggest novel attention-based explanations for empirical phenomena that are associated with characteristic shapes of CPT's probability-weighting function, such as the certainty effect, the fourfold pattern, and the description-experience gap. More generally, we add to the integration of two prominent computational frameworks for decision making under risk.

5.1 Introduction

Psychological theory is often depicted as fragmented to a high degree, with some even going so far as to claim psychology has *no* theory (Gigerenzer, 2010). Others have argued that the replication crisis in psychology is rooted in the lack of overarching theoretical frameworks (Muthukrishna & Henrich, 2019). Even within sub-fields, such as research on decision making under risk, key constructs of existing models are typically specific to their theoretical framework. Each framework operates within closely circumscribed conceptual bounds, making it difficult to identify connections between different theories.

For instance, Cumulative Prospect Theory (CPT, Tversky & Kahneman, 1992), belongs to the class of neo-Bernoullian models of decision making under risk, which revolve around the economic concept of utility. CPT encodes choice patterns by assuming systematic distortions of outcome and probability information, formalized in terms of psychoeconomic functions. Specifically, the valuation of outcomes is described in a *value function*, and the impact of the outcomes on the desirability of options is captured in decision weights derived from a nonlinear *probability-weighting function*. The particular shape of the probability-weighting function allows researchers to assess whether probabilistic events receive too much or too little weight, compared to linear weighting using objective probabilities. Thereby CPT accommodates intriguing phenomena of risky choice, such as the certainty effect—the tendency to systematically overweight safe outcomes compared to merely probable ones.

On the other hand, the attentional Drift Diffusion model (aDDM, Krajbich et al., 2010; Krajbich & Rangel, 2011) belongs to the class of sequential sampling models, which rely on very different key constructs. Sequential sampling models stem from the literature on perceptual discrimination but are now applied in other domains, including risky choice (cf. Busemeyer & Townsend, 1993; Diederich & Trueblood, 2018; Johnson & Busemeyer, 2005). They describe the decision-making process as an accumulation of information over time until the evidence in favor of one alternative exceeds a threshold, resulting in a choice. A recently developed variant, the aDDM, formalizes how attention affects the evaluation and comparison of options: By assuming that evidence in favor of an option accumulates at a faster rate while this option is in the focus of attention the aDDM can, for instance, explain why people tend to choose the option that they look at longer (Armel et al., 2008; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Glöckner et al., 2012; Glöckner & Herbold, 2011; Konovalov & Krajbich, 2016; Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011; Shimojo et al., 2003; Stewart et al., 2016), even if their attention is exogenously manipulated (Armel et al., 2008; Shimojo et al., 2003), and why people seem to increasingly look at the option that they end up choosing during the process of preference formation—a phenomenon known as the gaze cascade (Shimojo et al., 2003).

Hence, both CPT and aDDM provide powerful tools to sharpen the understanding of empirical phenomena in their respective fields—by expressing these phenomena in terms of their particular conceptual language. Yet, this sharp conceptual focus also creates blind spots. For instance, both the certainty effect and the gaze cascade have driven major theoretical innovations within one tradition, yet they seem to be nearly irrelevant to the other one. How does the certainty effect emerge on a process level, and does attention contribute to this? Does the gaze cascade have a distinctive signature in CPT's probability-weighting function? Questions of this kind simply do not arise, as an artifact of the separation between the two theoretical traditions: The predominant way of reasoning in each tradition determines which empirical phenomena even get considered. Indeed, the particular conceptual language in which theories are expressed can make it difficult to formulate certain problems (cf. Broadbent, 1984). This echoes Marr's (1982) sentiment that different ways of expressing the same information make some aspects of it more explicit while pushing others to the background—and thereby crucially determine how the information can be further utilized and understood. Therefore, many opportunities to exploit potentially complementary insights from the world of neo-Bernoullian and sequential sampling models may have gone unnoticed. Remarkably little is known about whether and how the neo-Bernoullian and the sequential sampling frameworks—or individual models and constructs within them—map onto each other.

Here we showcase an approach for overcoming this divide. First, we consider how core assumptions in CPT and aDDM came about historically. Although not much exchange took place during their evolutions, both traditions faced similar challenges, which led to the introduction of nonlinear probability-weighting functions and attentional weighting, respectively. Besides this historical perspective, formal similarities suggest that probability-weighting functions in CPT may be able to account for the effects of attentional biases in the aDDM. To test this, we conduct a cross-theory parameter recovery, by simulating data in the aDDM and fitting it in CPT. Indeed, the behavioral consequences of attentional biases in the aDDM—including both choices and response times—have highly systematic signatures in the shape of CPT's probability-weighting function. That is, the two traditionally disconnected theoretical constructs—nonlinear probability weighting in CPT and attentional biases in aDDM—can account for the same behavioral regularities.

After establishing this mapping theoretically by simulation and recovery, we show that it also holds empirically. Specifically, in a re-analysis of data on decisions from experience, we find that attentional biases towards safe or risky options during information search have highly systematic signatures in empirical probability-weighting functions, strikingly similar to those identified in the parameter recovery. Hence, our integrative theoretical efforts open up a novel, process-based perspective for understanding behavior in a paradigm that has long been scrutinized in terms of apparent probability weighting patterns. Beyond decision from experience, our results also suggest innovative explanations for several other seminal phenomena of risky choice, which have so far mainly been discussed in terms of CPT: The probability weighting patterns characteristic of the certainty effect, the fourfold pattern and the description-experience gap may be consequences of systematic attentional biases. Moreover, our findings also have important conceptual implications: Parameters of CPT's weighting function are often interpreted psychologically, in terms of probability sensitivity and optimism or pessimism (Gonzalez & Wu, 1999). Our results suggest a different interpretation in terms of attentional biases.

Next we describe central assumptions in CPT and aDDM, and how they evolved. This illustrates the key differences between the models, but also points towards the potential for connecting them.

5.1.1 Neo-Bernoullian Models of Risky Choice: The Origins of Cumulative Prospect Theory

The tradition of (neo-)Bernoullian models of risky choice reaches back to the 18th century, when Daniel Bernoulli replaced the notion of expected value maximization by the expected utility principle (1738/1954)[1], which was later axiomatized by von Neumann and Morgenstern (1945). In what became subsequently known as expected utility (EU) theory, Bernoulli posited that the desirability of items should not be assessed based on their objective value, but the subjective utility each individual would derive from them. Further assuming that the same increase in value would be less significant for a more wealthy person, he proposed a concave utility function—a concept still featured in several modern theories of decision making (Birnbaum, 2005; Fishburn, 1970; Lopes,

[1] The English translation of Bernoulli's work originally written in Latin in 1738 was published in 1954.

1987; Tversky & Kahneman, 1992). The most widely known modern variant is the *value function* of prospect theory (PT, Kahneman & Tversky, 1979) and CPT (Tversky & Kahneman, 1992). Here, in contrast to EU theory, the carriers of subjective utility are no longer absolute end states, but changes in value compared to a reference point. CPT's value function is concave for gains and convex for losses, assuming that such changes in value are more difficult to discriminate the further they are away from the reference point. Moreover, the value function is steeper for gains than for losses, thus assuming loss aversion.

While many neo-Bernoullian theories maintain the notion of a curved utility function, they revise EU in another important aspect—the weighting of probabilistic events. In EU, the utilities of possible outcomes are weighted by their objective probabilities. This principle provides a normative benchmark for maximizing expected utility, but it is often violated by human decision makers. For instance, in choices between a risky prospect, offering the chance to win (or lose) some amount x with probability p and nothing otherwise, and a safe prospect, offering to win (or lose) some amount y with certainty, people exhibit the *fourfold pattern of risk attitudes*: They are risk averse for high-probability gains and low-probability losses, but risk seeking for low-probability gains and high-probability losses (Tversky & Fox, 1995; Tversky & Kahneman, 1992). In further violation of EU, most people prefer a small safe gain over a more valuable risky gain, but when offered a choice between two risky gains, they prefer the one with the higher EV. This phenomenon, known as the *certainty effect*, suggests that people overweight safe outcomes relative to merely probable ones (Allais, 1953; Kahneman & Tversky, 1979; Tversky & Kahneman, 1986). To account for these and other violations of EU, PT (Kahneman & Tversky, 1979) and later CPT (Tversky & Kahneman, 1992) replaced objective probabilities as weights on the subjective utilities by *decision weights*. Decision weights capture the impact of an event's probability on its desirability, and are derived from an inverse S-shaped *probability-weighting function*. This weighting function implies that small probabilities are overweighted, whereas moderate to large probabilities are underweighted—capturing the fourfold pattern. Moreover, differences in probability have less impact the further they are away from the reference points of certainty and impossibility. For instance, the difference in probability between .9 and 1 has a greater impact on the event's desirability than the difference between .4 and .5—although the increment is .1 in both cases—thus capturing the certainty effect. An exemplary inverse S-shaped weighting function is illustrated in Figure 5.1.

The introduction of nonlinear probability-weighting functions marked a major paradigm shift in the world of neo-Bernoullian modeling: Rigid constraints qualified EU to prescribe how idealized economic agents could maximize expected utility. Then, CPT sacrificed adherence to strict maximization for the sake of improved descriptive validity, by allowing for more flexible, nonlinear weighting. Consequently, CPT has become one of the most widely applied and influential descriptive models of risky choice.

Subsequently, the functional form of the nonlinear weighting function was continually refined based on formal and empirical grounds (cf. Prelec, 1998; Stott, 2006; Tversky & Fox, 1995). This resulted in a variety of weighting functions, governed by a curvature parameter γ, and in some cases by an additional elevation parameter δ (cf. Figure 5.4, more details on differences between specific weighting functions are provided below). These parameters are commonly used to measures distinct psychological constructs. Tversky and Kahneman (1992) interpreted the curvature as an indicator of probability sensitivity. Later, the elevation parameter of two-parameter weighting functions became commonly understood as a measure of optimism or pessimism (Gonzalez & Wu, 1999; Lattimore et al., 1992). We will identify possible alternative interpretations for these parameters in terms of attentional processes.

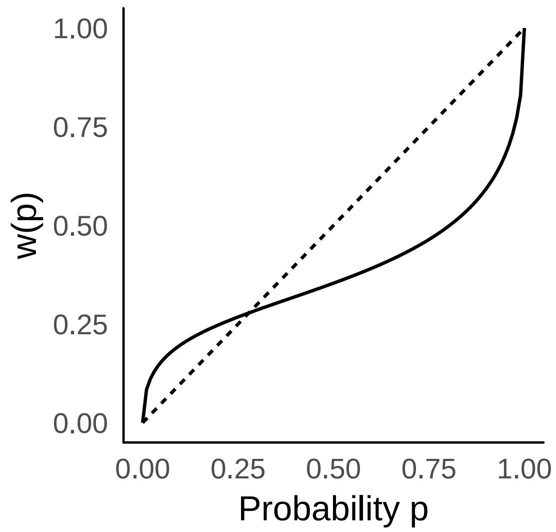

Figure 5.1: An exemplary inverse S-shaped weighting function like the one used by Tversky & Kahneman (1992) when introducing CPT. The dashed identity line serves as a reference for the objective weighting of probabilities, as assumed in EU.

5.1.2 Sequential Sampling Models: The Origins of Attentional Drift Diffusion Models

Sequential sampling models account for both choice behavior and response times by formalizing how decision makers gather and integrate information on the options over time. They originate from theories of ideal performance, originally developed as solutions to optimization problems in engineering (Wallis, 1980): Static signal detection models (SDT) captured how ideal observers can maximize accuracy in simple perceptual tasks, such as judging whether a stochastic stimulus contains only noise or some signal component (Swets, 1961; Tanner Jr. & Swets, 1954). Sequential probability ratio tests (SPRT, cf. Ashby, 1983; Stone, 1960; Wald & Wolfowitz, 1948) extend the notion of the optimal observer in SDT along the temporal dimension: Instead of evaluating the signal strength or value of the stimulus in a single step, evidence is sampled repeatedly in a discrete random walk. The Drift Diffusion Model (DDM, Ratcliff, 1978) is the continuous-time analogue of discrete random walks (Bogacz et al., 2006; Ratcliff & Smith, 2004; Ratcliff & Tuerlinckx, 2002). Both SPRT and DDM can optimize response speed for a desired level of accuracy, with higher accuracy coming at the cost of longer RTs (Bogacz et al., 2006). Therefore both SPRT and DDM provide a mechanistic explanation for speed-accuracy trade-offs, a key behavioral regularity in many domains, such as perception, memory and higher cognition (Reed, 1973; Wickelgren, 1977). Many areas of experimental psychology applied, extended and refined the class of sequential sampling models for paradigms including perceptual judgments (Link & Heath, 1975; Ratcliff & Rouder, 1998), recognition memory (Ratcliff, 1978), lexical decision tasks (Ratcliff et al., 2004), categorization (Nosofsky & Palmeri, 1997), and—most relevant for our current purposes—risky choice (Busemeyer & Townsend, 1993; Diederich & Trueblood, 2018; Johnson & Busemeyer, 2005).

However, since the optimal but comparably restrictive predictions of early sequential sampling models were found incompatible with the complex empirical relationship between RT distributions and choice behavior, the model parameters were rendered increasingly flexible (Laming, 1968; Ratcliff, 1978; Ratcliff & Smith, 2004; Ratcliff & Tuerlinckx, 2002). Among the most note-

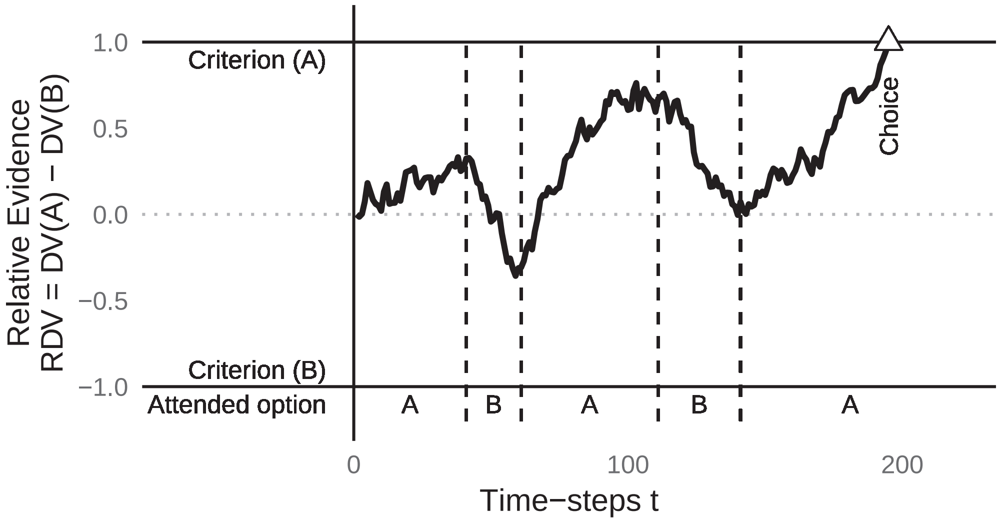

Figure 5.2: An exemplary simulated aDDM process. The relative evidence in favor of option A versus option B accumulates over discrete steps of time. During each fixation, evidence in favor of the currently fixated option is amplified, generating an advantage for the predominantly fixated option. When evidence exceeds one of the choice criteria the corresponding option is chosen.

worthy recent extensions of the framework are variants of DDM that account for the impact of visual attention on choice: In a wide variety of choice domains (Smith & Krajbich, 2018) people tend to choose the option that they look at longer (Armel et al., 2008; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Glöckner et al., 2012; Glöckner & Herbold, 2011; Konovalov & Krajbich, 2016; Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011; Shimojo et al., 2003; Stewart et al., 2016), even if their attention is exogenously manipulated (Armel et al., 2008; Ghaffari & Fiedler, 2018; Newell & Le Pelley, 2018; Shimojo et al., 2003), and over the time course of preference formation, individuals seem to increasingly look at the item they end up choosing (a phenomenon known as the *gaze cascade*, cf. Mullett & Stewart, 2016; Shimojo et al., 2003). To accommodate these striking findings Krajbich et al. (2010) introduced a mechanism of option-specific attentional weighting to the sequential sampling framework: In what is now commonly referred to as the attentional Drift Diffusion Model (aDDM, cf. Krajbich et al., 2012; Krajbich & Rangel, 2011),[2] evidence for an option accumulates at a faster rate while that option is in the focus of attention. An exemplary evidence accumulation trajectory as assumed by the aDDM is illustrated in Figure 5.2. Under aDDM assumptions, the proportion of time spent attending to the options in the choice set modulates their relative desirability. Thereby, the aDDM can account for the previously delineated empirical findings: Options that receive more attention are more likely to be chosen, and the model predominantly tends to choose the item that was looked at last (thus creating the impression of a temporally evolving gaze cascade, cf. Mullett & Stewart, 2016).

Notably, this boost in descriptive accuracy sacrificed adherence to earlier notions of optimal performance: While the simple (non-attentional) random walk serving as a baseline for the aDDM can implement an optimal SPRT, that is, a pure maximization strategy, the aDDM allows for systematic deviations from this normative benchmark (Krajbich & Rangel, 2011): Excess time spent attending to an option can increase the probability of choosing the option, even if it is objectively inferior. Hence, unless attention is systematically biased towards the highest valued,

[2]We subscribe to this terminology although referring to these types of models as aDDM invokes the notion of continuous time, which is at odds with the original formalization of aDDM as a discrete random walk (Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011).

objectively preferable option, systematic deviations from maximization behavior emerge. This also holds empirically: Individuals who show a stronger association between gaze and choice behavior,[3] perform worse at choosing the best item in the choice set (Thomas et al., 2019). Hence, although the aDDM is not explicitly framed as a theory of choice biases or deviations from optimality, it makes an important contribution regarding choice phenomena that are typically described in such a way: It (implicitly) identifies option-specific attentional biases as a possible determinant of systematic deviations from pure maximization.

5.1.3 The Potential for Theory Integration: Overlooked Commonalities of the Two Modeling Traditions

The historical viewpoint illustrates that the neo-Bernoullian and sequential sampling frameworks are largely disconnected, and to some extent also explains why this is the case: Both traditions started out to address fundamentally different types of choice tasks, they encountered their own empirical challenges, and established and refined their own conceptual language accordingly. It is not immediately obvious why it might be interesting—or even possible—to translate these languages into one another. A closer look, however, reveals several commonalities between both frameworks.

For instance, although the perceptual discrimination tasks of early SDT models are not commonly described as risky choice, they required to distinguish and evaluate stochastic stimuli. Conversely, for the economically rational agents of early utility models, risky choice tasks reduce to the psychophysical problem of distinguishing noisy distributions, in order to identify the one with the higher expected value—the standard problem solved by SDT models. Early verbal descriptions of prospect theory as a model of the *psychophysics of chance* (cf. Kahneman & Tversky, 1984) highlight this common essence of the problems addressed within both traditions.

Besides being applicable to similar choice problems, both traditions also faced similar hurdles when trying to accommodate empirical behavior. Early notions of optimal performance were sacrificed in favor of descriptive accuracy: CPT managed to account for systematic empirical deviations from utility maximization, as prescribed by EU, by introducing nonlinear probability weighting. The aDDM managed to account for preferences in favor of options that may be objectively inferior, but receive more attention, by introducing attentional weighting. While decision weights in CPT distort the representations of options themselves, the attentional weights in aDDM distort the comparison between the options. In essence, however, both types of distortions generate a systematic advantage for one of the options, which is not necessarily justified under a maximizing policy. Thus CPT's decision weights and aDDM's attentional weights equip their respective framework with analogue capacities—suggesting that both constructs may capture the same behavioral regularities.

That is, it might be possible to bridge the conventional divide between CPT and aDDM in a very fruitful manner: The behavioral consequences of overweighting options that receive more attention in the aDDM might have systematic signatures in CPT's probability-weighting function. Conversely, cornerstone phenomena of risky choice that are typically described by characteristic shapes of CPT's probability-weighting function (e.g. the certainty effect, the fourfold pattern), might be explicable by systematic attentional biases. That is, establishing a correspondence between disparate theoretical constructs might make it possible to obtain a more holistic understanding of phenomena so far studied exclusively in within one (native) tradition. Regardless, this rich possibility has thus far been overlooked.

[3] meaning that they implement the aDDM assumptions to a stronger degree

5.1.4 Outline

In what follows, we investigate to which extent probability weighting in CPT can reflect the effects of attentional weighting in aDDM. To carve out the shared essence of both constructs, we first introduce aDDM and CPT formally and explain how both attentional biases and decision weights can make risky or safe options appear more or less attractive than justified by their objective value, and thereby modulate choice behavior. We then derive specific hypotheses how systematic changes in the aDDM's choice behavior due to attentional biases to safe or risky options might be reflected in CPT's probability-weighting function.

To develop and test our argument, we focus on choices between safe and risky options, a paradigm often employed in behavioral experiments on risky choice, and sometimes thought to measure risk preferences (e.g., Rutledge et al., 2016). We define a safe option as offering one certain outcome o_{safe}, and a risky option as consisting of a high outcome $o_{high,risky}$ and a low outcome $o_{low,risky} < o_{high,risky}$ with the probabilities p_{high} and $p_{low} = 1 - p_{high}$. Illustrating our argument in this type of choice problem allows us to keep formal complexity to a minimum. We later elaborate why and how our argument also extends to choices between two risky options, and to the domain of losses.

5.1.5 The Impact of Attentional Biases on the Comparison between Safe and Risky Options in aDDM

The aDDM is a sequential sampling model which assumes that evidence in favor of an option is accumulated at a faster rate whenever this option is attended to (Krajbich et al., 2010; Krajbich & Rangel, 2011). This model can formalize the process of preference formation in choices between safe and risky options as follows.

Evidence in favor of the safe option DV_{safe} and evidence in favor of the risky option DV_{risky} evolve over time. On each time-step t of the accumulation process, either the safe or the risky option is in the focus of attention. The probability p_{t_s} of attending to the safe option on each step defines the attentional bias in the process. Both options are inspected equally often if $p_{t_s} = 0.5$. If $p_{t_s} < 0.5$, there is an attentional bias to the risky option, and if $p_{t_s} > 0.5$, there is an attentional bias to the safe option. On time-steps t where the safe option is attended to DV_{safe} and DV_{risky} evolve according to

$$\begin{aligned} DV_{safe}(t) &= DV_{safe}(t-1) + d * \theta_{attended} * o_{safe} + \epsilon \\ DV_{risky}(t) &= DV_{risky}(t-1) + d * \theta_{unattended} * o_{i,risky} + \epsilon \end{aligned} \tag{5.1}$$

and on time-steps t where the risky option is attended to DV_{safe} and DV_{risky} evolve according to

$$\begin{aligned} DV_{safe}(t) &= DV_{safe}(t-1) + d * \theta_{unattended} * o_{safe} + \epsilon \\ DV_{risky}(t) &= DV_{risky}(t-1) + d * \theta_{attended} * o_{i,risky} + \epsilon \end{aligned} \tag{5.2}$$

On each step t, one outcome of the safe and the risky option (o_{safe} and $o_{i,risky}$) are sampled as evidence, scaled by the constant $d = 0.01$, with added Gaussian noise $\epsilon \sim \mathcal{N}(0, \sigma^2)$. The i different outcomes $o_{i,risky}$ of the risky option are sampled proportionally to their probabilities $p_{i,risky}$.[4] The parameters $\theta_{attended}$ and $\theta_{unattended}$ capture that evidence for each option evolves at

[4]Instead of sampling individual outcomes proportional to their objective probability, this process could also be implemented by sampling the options' EVs. This alternative implementation is described in chapter 4. Due to the law of large numbers both implementations behave alike, except if the total number of samples preceding the choice

a slower rate whenever the alternative option is attended to. The evidence DV for the currently attended option on each step t evolves with $\theta_{attended} = 1$. Evidence for the unattended option evolves with $\theta_{unattended} < 1$. Therefore, over time, evidence in favor of an option accumulates at a faster rate if attention is biased towards this option—a mechanism of option-specific attentional weighting.[5]

Once the difference $DV_{safe} - DV_{risky}$ reaches the upper or the lower decision boundary—indicating that the evidence in favor of one option exceeds the evidence in favor of the other option by a sufficient magnitude—a choice is made. Attentional biases can shift this comparison in favor of the option that is in the focus of attention for a larger proportion of time and thus increase the probability of choosing this option.

5.1.6 The Impact of Decision Weights on the Comparison between Safe and Risky Options in CPT

In CPT, each option's objective outcomes are transformed into subjective values according to the value function v

$$v(o_i) = \begin{cases} \mathrm{o}_i^{\alpha}, & \text{if } \; o_i \geq 0 \\ \text{-}(\mid o_i \mid^{\alpha}), & \text{if } \; o_i < 0 \end{cases} \tag{5.3}$$

with $\alpha \in [0, 1]$, such that v is concave for gains and convex for losses. The overall valuation V of an option is defined as the sum across all outcomes' subjective values, weighted by cumulative decision weights π (details below):

$$V = \sum_{i=1}^{n} \pi_i \times v(o_i) \tag{5.4}$$

To derive choice probabilities from the CPT-based valuation V_{safe} and V_{risky} of the safe and the risky option the difference $V_{safe} - V_{risky}$ is typically entered into a stochastic choice rule. For instance, the logit choice rule (Stott, 2006) defines the probability that the safe option is chosen over the risky option as

$$p(safe, risky) = \frac{1}{1 + e^{-\rho[V_{safe} - V_{risky}]}} \tag{5.5}$$

with $\rho > 0$. The response noise parameter ρ captures to which extent choices are determined by the difference between the options' valuations. Under $\rho = 0$ the choice probability is 0.5. With higher values of ρ the probability of choosing the option with the higher valuation increases.

Here we focus on how probability weighting can affect the relative attractiveness of safe and risky options. The decision weights π of all outcomes within a pure-domain risky gamble add up to 1. Hence probability weighting can be interpreted as re-distributing the total probability mass of 1 across the outcomes. The decision weight π for each positive outcome o_i is defined as the difference between the probability of obtaining an outcome at least as good as o_i and the

is extremely low. Here we describe the variant that samples individual outcomes, since it more closely resembles the process of preference formation in the sampling paradigm in decision from experience (Hertwig & Erev, 2009; Wulff et al., 2018), which we turn to later.

[5] In the most extreme case $\theta_{unattended}$ is set to zero, such that on steps where the safe option is inspected evidence DV_{safe} evolves with $\theta = 1$, and evidence DV_{risky} does not change at all. Krajbich and Rangel (2011) assume that $\theta_{unattended}$ can vary in [0,1]. Also note that under $\theta_{unattended} = 1$ the aDDM reduces to a standard DDM[6], where attentional biases do not distort the comparison between the options. In this case the model can implement an optimal SPRT, where decision quality (maximization performance) is only impaired by non-systematic noise. That is, for $\theta_{unattended} = 1$ the model predicts no systematic deviations from EV maximization. The impact of $\theta_{unattended}$ is addressed in Appendix D.1 in more depth.

probability of obtaining a strictly better outcome, both transformed by the probability-weighting function w.[7] Hence, for a two-outcome risky gamble in the domain of gains, the decision weights of the higher and lower outcome are given by

$$\begin{aligned}\pi_{high} &= w(p_{high})\\ \pi_{low} &= w(p_{low} + p_{high}) - w(p_{high})\\ &= 1 - \pi_{high}\end{aligned} \tag{5.6}$$

and the total valuation V_{risky} of such a risky option is

$$\begin{aligned}V_{risky} &= \pi_{low} * v(o_{low,risky}) + \pi_{high} * v(o_{high,risky})\\ &= \underbrace{\pi_{high}}_{\substack{decision\\ weight}} * \underbrace{[v(o_{high,risky}) - v(o_{low,risky})]}_{\substack{potential\ increase\\ in\ utility}} + \underbrace{v(o_{low,risky})}_{\substack{minimum\\ utility}}\end{aligned} \tag{5.7}$$

Thus V_{risky} depends on the decision weight of the higher outcome π_{high}. Under linear probability weighting, π_{high} equals the objective probability p_{high}, such that weighting in CPT reduces to EU assumptions. Under nonlinear probability weighting, π_{high} can be smaller (larger) than p_{high}. In particular, given a weighting function that predominantly runs below (above) the identity line, the chance to obtain the higher outcome is assigned less (more) weight than it objectively deserves. That is, if a weighting function predominantly *underweights* (*overweights*) probabilities, it systematically makes risky options appear less (more) attractive than objective weighting. This is illustrated in Figure 5.3.

By contrast, the valuation of the safe option is not affected by nonlinear probability weighting, because the decision weights of safe outcomes always equal 1:

$$\begin{aligned}V_{safe} &= \pi_{p_{safe}} * v(o_{safe})\\ &= 1 * v(o_{safe})\end{aligned} \tag{5.8}$$

Hence, in choices between a safe and a risky option, nonlinear weighting functions can selectively modulate the valuation of the risky option while leaving the valuation of the safe option unaffected. Therefore, they can shift the comparison between safe and risky options ($V_{safe} - V_{risky}$) in favor of or against the risky option, and thereby in- or decrease the probability of choosing the risky option. Note that by contrast, the value function v always affects the valuation of both options (except if $o_{safe} = 0$), and hence can not modulate the relative attractiveness of safe and risk options as *selectively* as the weighting function. Thus, when developing our hypotheses about corresponding constructs in aDDM and CPT, we mainly focus on probability weighting.

5.2 Simulation Analyses: Do Attentional Biases in aDDM Affect Probability Weighting in CPT?

5.2.1 Predictions

We propose that nonlinear probability-weighting functions in CPT may be able to accommodate the behavioral consequences of option-specific attentional biases in the aDDM. For instance, given

[7] Applying the probability-weighting function to *cumulative* probabilities in this manner avoids violations of stochastic dominance which are implicit in non-cumulative weights, as used in the original version of Prospect Theory (Kahneman & Tversky, 1979; Lattimore et al., 1992). In original PT this issue was resolved by removing dominated options from the choice set during the editing phase.

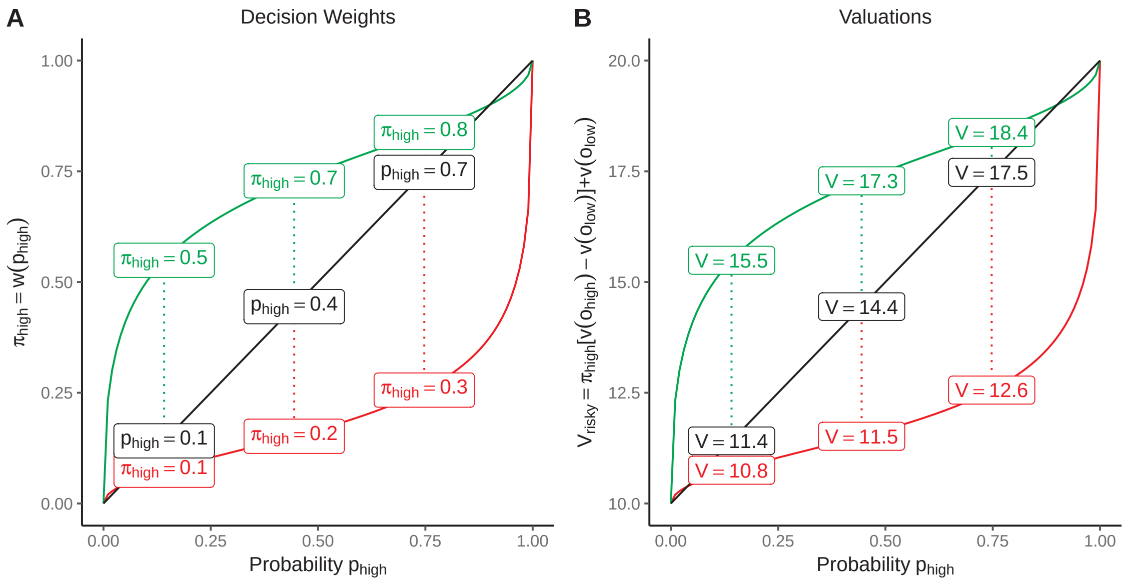

Figure 5.3: How non-linear probability weighting affects the valuation of risky options, for risky options with different exemplary values of p_{high}. A) The black diagonal illustrates linear weighting, where the decision weight π_{high} equals the objective probability. The green weighting function predominantly runs above the diagonal, and thus predominantly overweights probabilities. Hence most π_{high} are larger than the corresponding objective probabilities. The red weighting function predominantly runs below the diagonal, and thus predominantly underweights probabilities. Hence most π_{high} are smaller than the corresponding objective probabilities. B) How does probability weighting affect the valuation V_{risky} of risky options (in the exemplary case with $o_{high} = 20$ and $o_{low} = 10$)? Under linear weighting (black diagonal) V_{risky} equals the objective valuation under EU. Under the green weighting function, which predominantly overweights probabilities, V_{risky} is typically larger than the objective valuation. Under the red weighting function, which predominantly underweights probabilities, V_{risky} is typically smaller than the objective valuation. By contrast, the valuation of safe options with $p_{safe} = 1$ remains the same under all three weighting functions. Hence non-linear probability weighting can selectively amplify or attenuate the attractiveness of risky compared to safe options

an attentional bias to the risky option, the aDDM accumulates evidence in favor of the safe option at a slower rate, thus increasing the probability of choosing the risky option. Weighting functions in CPT may be able to accommodate this pattern by assuming a shape that makes the risky option appear more attractive, thus shifting the comparison in its favor and increasing the probability of choosing it. This can be achieved if probabilities are predominantly overweighted, relative to linear weighting. Conversely, weighting functions may be able to reflect attentional biases towards the safe option by assuming parameter settings that make risky options appear unattractive. This can be achieved if probabilities are predominantly underweighted. Hence, attentional biases in aDDM may have systematic signatures in probability weighting in CPT. Generally speaking, weighting functions in CPT should be able to reflect option-specific attentional biases in the aDDM to the extent that they are capable of modulating the relative attractiveness of the risky and safe options.

Differential Effects for Different Types of Weighting Functions

We test this argument using four different weighting functions—including highly flexible two-parameter weighting functions and less flexible one-parameter weighting functions. These weighting functions differ in their capacities for modulating the relative attractiveness of safe and risky options. Consequently, if our argument holds, some—but not all—weighting functions should be

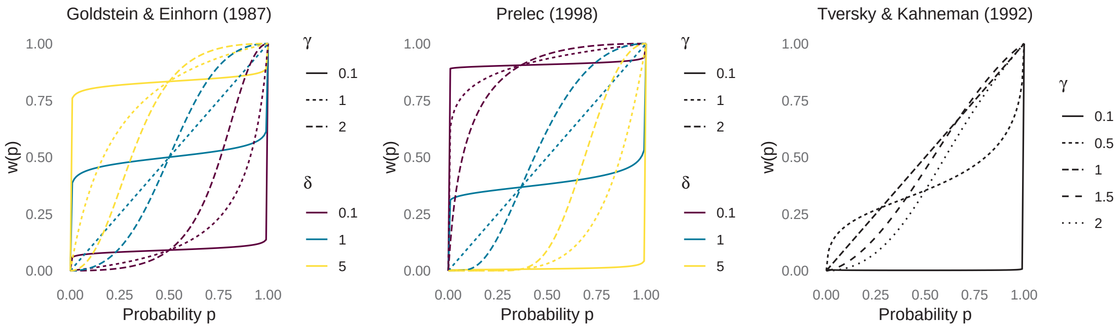

Figure 5.4: Weighting functions by Goldstein & Einhorn (1987), Prelec (1998) and Tversky & Kahneman (1992) for a range of parameter settings.

able to reflect option-specific attentional biases. We derive whether and how (i.e., based on which parameter settings) each of the four weighting functions can be expected to reflect option-specific attentional biases. These predictions are summarized in Table 5.1.[8]

Two-parameter weighting functions The weighting functions by Goldstein and Einhorn (1987)

$$w_{GE87}(p) = \frac{\delta * (p^\gamma)}{\delta * p^\gamma + (1-p)^\gamma} \tag{5.9}$$

and the weighting function by Prelec (1998)

$$w_{PR98}(p) = e^{-\delta(-log(p))^\gamma} \tag{5.10}$$

are shaped by two parameters $\gamma \in [0, 2]$ and $\delta \geq 0$ (cf. left and middle panel of Figure 5.4). The parameter δ governs the elevation of the weighting functions and is the key parameter distorting the relative attractiveness of risky options. A more (less) elevated weighting function mostly runs above (below) the identity line, such that most probabilities are overweighted (underweighted). Hence a higher (lower) elevation tends to make risky (safe) options appear more attractive. Therefore we expect two-parametric weighting functions to reflect greater attentional biases to risky over safe options in terms of a higher elevation, and vice versa. Note in Figure 5.4, that in Prelec's weighting function, *lower* values of δ entail a *higher* elevation, while in Goldstein and Einhorn's weighting function, *higher* values of of δ entail a *higher* elevation. Thus, while in both cases risky options appear more attractive when the weighting function is more elevated, this feature is mapped on the parameter space differently. Hence, if greater attentional biases to risky options indeed entail a more elevated weighting function, this should be reflected in higher values on δ in Goldstein and Einhorn's (1987) weighting function, but in lower values on δ in Prelec's (1998) weighting function. Psychologically, a higher or lower elevation is commonly interpreted in terms of optimism or pessimism, respectively (Abdellaoui et al., 2010; Gonzalez & Wu, 1999).

The parameter γ determines the curvature of both weighting functions. In Prelec's (1998) weighting function, lower values of γ make risky options appear less attractive. Hence, more attention paid to the safe option is expected to be reflected in decreasing values of γ. In Goldstein and Einhorn's (1987) weighting function, the effects of γ depend on the elevation δ. If $\delta < 1$ then lower values of γ make safe options even more attractive. If $\delta > 1$ then lower values of γ make risky

[8]In the main text we briefly summarize the key predictions for each weighting function. These predictions are informed by an in-depth discussion of how each weighting function distorts the valuation of risky options under different parameter combinations, provided in Appendix D.4.

Table 5.1: How Different Weighting Functions Are Expected to Reflect Option-Specific Attentional Biases Implemented in the aDDM for Choices Between Safe and Risky Options.

Weighting Function	Predicted Response to Increasing the Attentional Bias To The Safe Option	Predicted Response to Increasing the Attentional Bias To The Risky Option
Goldstein and Einhorn (1987)	Decrease in δ ($\delta < 1$)	Increase in δ ($\delta > 1$)
	Decrease in γ ($\gamma < 1$)	Decrease in γ ($\gamma < 1$)
Prelec (1998)		
- two parameters	Increase in δ ($\delta > 1$)	Decrease in δ ($\delta < 1$)
	Decrease in γ ($\gamma < 1$)	Increase in γ ($\gamma > 1$)
- one parameter (with $\delta = 1$)	Less sensitive to extreme attentional biases than two-parameter variant	
	Moderate bias: Decrease in γ ($\gamma < 1$)	Moderate bias: Increase in γ ($\gamma > 1$)
Tversky and Kahneman (1992)	Stronger deviation of γ from 1 (in either direction)	Not sensitive to bias to risky option

options even more attractive. Therefore, more extreme attentional biases—in either direction—are expected to be reflected in decreasing values of γ, relative to the neutral value of $\gamma = 1$. Note that more linear (less curved) weighting functions are commonly thought to reflect greater probability sensitivity (Gonzalez & Wu, 1999). Table 5.1 summarizes these predictions.

One-parameter weighting functions Prelec's weighting function is sometimes reduced to a one-parameter form by fixing the elevation δ at 1

$$w_{PR98_1par}(p) = e^{-(-log(p))^{\gamma}} \tag{5.11}$$

and Tversky and Kahneman (1992) also used a one-parametric weighting function in their seminal paper introducing CPT:

$$w_{TK92}(p) = \frac{p^{\gamma}}{(p^{\gamma} + [1 - p^{\gamma}])^{1/\gamma}} \tag{5.12}$$

Both one-parameter weighting functions are shaped by a curvature parameter $\gamma \in [0, 2]$ (cf. middle and right panel of Figure 5.4). For both functions, γ can be set such that the function mostly runs below the identity line, such that risky options tend to appear less attractive than under linear probability weighting. In Prelec's (1998) weighting function, lower values of γ tend to make risky options appear less attractive. Hence, we expect attentional biases to the safe option to be reflected in decreasing values of γ. In Kahneman and Tversky's (1992) weighting function, values of γ that deviate from 1 more (in either direction) make risky options appear less attractive, compared to linear weighting. Hence, attentional biases to the safe option are expected to be reflected in values of $\gamma \neq 1$.

Moreover, the one-parameter weighting function by Prelec (1998), but not the one by Tversky and Kahneman (1992), can assume shapes that run mostly above the identity line, such that risky options tend to appear more attractive than under linear weighting. Hence, we expect that the one-parametric weighting function by Prelec (1998), but not the one by Tversky and Kahneman (1992), is also able to accommodate attentional biases towards the risky option over the safe option, in terms of its curvature. Overall, the one-parameter weighting functions tend to under- or overweight probabilities less strongly than the two-parameter weighting functions with $\delta \neq 1$. Hence, the one-parametric weighting functions may be less capable of reflecting very pronounced attentional biases. These predictions are summarised in Table 5.1.

5.2.2 Simulations

To test the proposed correspondence between attentional biases and probability weighting, we simulated choices and RTs for 150 decision problems offering a safe and a risky option, using the aDDM. The proportion of time that the synthetic participants spent attending to the safe and the risky option was systematically varied. To test whether the different weighting functions pick up on these option-specific attentional biases as predicted, hierarchical Bayesian CPT was fitted to the simulated choices for each level of attentional bias in the generative process.

Choice problems

150 pairs of safe and a risky options were generated using the following procedure: Both risky outcomes $o_{i,risky}$ were sampled from a uniform distribution ranging from 0 to 10, and rounded to 2 digits. The probability p_{high} of the higher outcome of the risky option was sampled from a uniform distribution ranging from 0 to 1, and the probability of the lower risky outcome was defined as $p_{low} = 1 - p_{high}$. All safe options consisted of one outcome o_{safe} with a probability of 1. The outcome o_{safe} for each safe option was sampled from a uniform distribution ranging from the smaller to the larger risky outcome on the same choice problem, and rounded to 2 digits. This serves to prevent dominated pairs of gambles (i.e., where all outcomes of one option are larger than all outcomes of the other option). The absolute EV differences between the options within each trial ranged from 0 to 5.69.

Data generation

The aDDM was used as a generative model. The probability p_{t_s} of attending to the safe option (i.e., sampling from its payoff distribution) on each step was systematically varied from .1 to .9 in increments of .1. To increase the resolution of our analysis for moderate attentional biases, we added two additional levels for p_{t_s} in the mid-range (at .45 and .55), resulting in a total of 11 levels of attentional bias. The parameter $\theta_{unattended}$ was set to 0.5, such that evidence for each option accumulated at half the speed when it was unattended (versus attended). This constitutes a moderate level of attentional amplification. The noise parameter σ was set to 0.075, a moderate level of noise. In Appendix D.1 we show that varying $\theta_{unattended}$ and σ does not change the general direction of attentional effects on choice—they merely become more or less pronounced. For each level of p_{t_s} choices of 25 synthetic participants on all 150 pairs of gambles were simulated, resulting in 11 data sets with $25 \times 150 = 3750$ choices each.

Resulting Behavior

We first describe the simulated behavioral consequences of attentional biases in the aDDM, in terms of behavioral risk preferences (the tendency to choose the safe option), decision quality (the tendency to choose the option with the higher EV), and response times (RTs, measured as the number of steps in the diffusion process until the boundary is hit). All three features are analysed with Bayesian Mixed Regression models implemented using the rstanarm package in R (Goodrich et al., 2018). All GLMERs include fixed effects for the attentional bias in the generative process, and random intercepts for each synthetic subject. We evaluate the credibility of the fixed effects by inspecting whether the 95% posterior intervals on the regression coefficients enclose zero.

Proportion of safe choices The proportion of safe (risky) choices increased with the attentional bias towards the safe (risky) option (cf. left panel of Figure 5.5). The statistical credibility of this

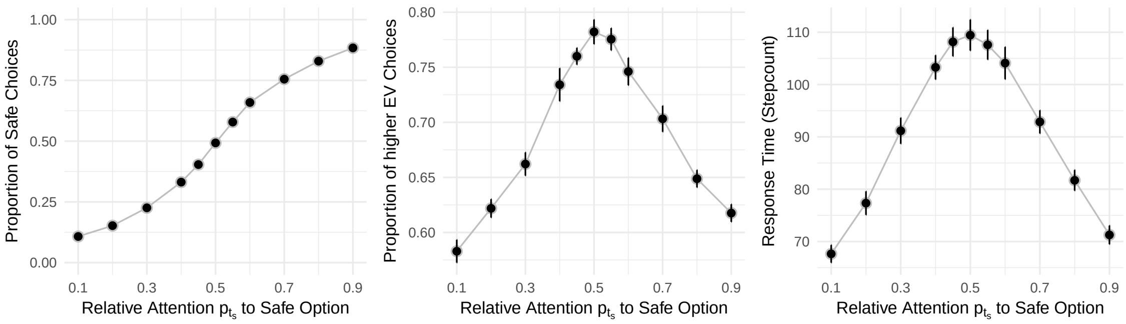

Figure 5.5: Risk preference, decision quality, and response times observed in the choice patterns generated in the aDDM, conditional on the relative attention to the safe option (attentional bias).

effect was corroborated in a Bayesian logistic mixed regression on the choice of the safe option as the outcome variable. The model included the relative attention to the safe option p_{t_s} as a fixed predictor. There was a strong credible effect of attention to the safe option on the tendency to choose that option ($\beta = 5.55$, 95% CI $[5.43, 5.67]$).

Proportion of higher EV option choices Decision quality, or maximization performance, decreased with increasingly extreme attentional biases, regardless of which option received more attention (cf. middle panel of Figure 5.5). The statistical credibility of this effect was corroborated in a Bayesian logistic mixed regression of decision quality as the outcome variable. The model included the absolute magnitude of the attentional bias (calculated as the absolute deviation of p_{t_s} from .5) as a fixed predictor. There was a credible negative effect of the magnitude of the attentional bias on decision quality ($\beta = -2.26$, 95% CI $[-2.42, -2.11]$). That is, as pointed out earlier, introducing attentional biases impairs maximization performance, because the probability of choosing the option that receives more attention increases, irrespective whether this option is objectively preferable.

Response times The RTs decreased with increasingly extreme attentional biases, regardless which option received more attention (cf. right panel of Figure 5.5). The statistical credibility of this effect was corroborated in a Bayesian mixed regression of RT as the dependent variable. The model included the absolute magnitude of the attentional bias (calculated as the absolute deviation of p_{t_s} from .5) as a fixed effect. There was a credible negative effect of the magnitude of the attentional bias on RT ($\beta = -108.32$, 95% CI $[-114.24, -102.13]$): Stronger attentional biases, regardless towards which option, led to faster choices.

5.2.3 Modeling in CPT

Each of the 11 data sets was fitted separately in four hierarchical Bayesian implementations of CPT. We considered four different versions of CPT, that differed in terms of the weighting function, using either the function by Goldstein and Einhorn (1987), Prelec (1998, both variants) or Tversky and Kahneman (1992). For all models, we estimated the parameters of CPT's value and weighting function and the parameter of a logit choice rule complementing the model. In the hierarchical models, each synthetic participant had a separate value on each parameter, and these individual-level parameters informed a group-level distribution. We use the group-level posterior estimates for the weighting function parameters γ and, if applicable, δ, to make inferences about the effects of attentional biases.

How CPT's Weighting Function Reflects Option-Specific Attentional Biases

Goldstein and Einhorn (1987) weighting function How does the weighting function by Goldstein and Einhorn (1987) reflect the different levels of attentional bias in data generated by the aDDM? The top panel in Figure 5.6 shows the means of the posterior distribution of δ and γ, for each level of attentional bias in the generative process, as well as the resulting weighting functions. As can be seen, the attentional bias in the generative process systematically affected the shape of the weighting function. The weighting function becomes less elevated with an increasing proportion of time spent attending to the safe option, relative to the risky option. This is reflected in lower values on δ. Attentional biases towards the risky option are reflected in $\delta > 1$ and attentional biases towards the safe option are reflected in $\delta < 1$. Conventionally, a higher elevation would be psychologically interpreted as greater optimism (or reduced pessimism, Abdellaoui et al., 2010; Gonzalez & Wu, 1999).

Moreover, increasingly extreme attentional biases (whether in favor of the safe or the risky option) are reflected in a more extreme curvature, that is, lower values of γ. Conventionally, a more extreme curvature would be psychologically interpreted as reduced probability sensitivity (Gonzalez & Wu, 1999; Tversky & Kahneman, 1992).

Unbiased attention is reflected by a neutral elevation (i.e., δ of approximately 1) and a neutral curvature (i.e., γ of approximately 1)—that is, linear probability weighting.

Prelec (1998) weighting function The attentional bias in the generative process also systematically affects the two-parameter variant of Prelec's (1998) weighting function. The bottom panel in Figure 5.6 shows the posterior mean parameter estimates for each level of attentional bias in the generative process, as well as the resulting weighting functions. The weighting function is less elevated when an increasing proportion of time is spent attending to the safe option, relative to the risky option. A less elevated weighting function would conventionally be interpreted in terms of greater pessimism (Gonzalez & Wu, 1999).

Moreover, an increasing proportion of time spent attending to the safe option is reflected in lower values of the curvature γ. Therefore, the weighting function is more convex (or inverse S-shaped) under stronger attentional biases towards the safe option, and more concave (or S-shaped) under stronger attentional biases towards the risky option. These more extreme curvatures under more extreme attentional biases would conventionally be interpreted in terms of reduced probability sensitivity (Gonzalez & Wu, 1999; Tversky & Kahneman, 1992).

Unbiased attention is reflected by a neutral elevation (i.e., δ of approximately 1) and a neutral curvature (i.e., γ of approximately 1)—that is, linear probability weighting.

Note that the two-parameter weighting functions by Prelec (1998) and by Goldstein and Einhorn (1987) assume very similar shapes to accommodate the same attentional biases. However, to achieve these similar shapes (more or less elevated and more or less extremely curved), the two weighting functions need to assume different parameter settings. This is due to the different functional definition of both weighting functions.

Moreover, we expected that the one-parameter variant of Prelec's weighting function would reflect moderate attentional biases in terms of its curvature, but that it would be limited in accounting for extreme attentional biases. The posterior parameter estimates show that this is indeed the case (cf. upper panel in Figure 5.7). The one-parameter form reflects moderate biases to the risky option in terms of higher values on the curvature parameter γ. However, as γ reaches its upper bound, more extreme biases towards the risky option cannot be distinguished anymore. As expected, fixing the elevation parameter, and thereby limiting this weighting function's flexibility

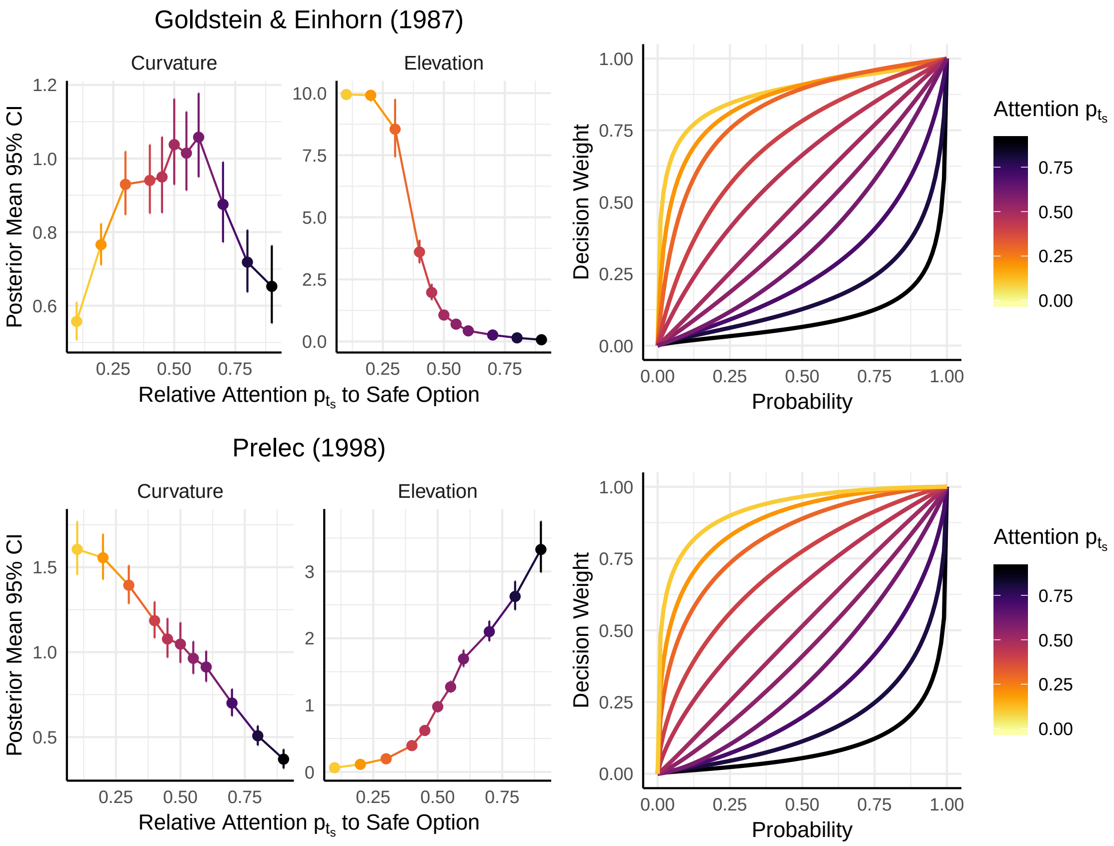

Figure 5.6: Parameter estimates and weighting functions for the two-parameter weighting functions by Goldstein & Einhorn (1987, top panel) and Prelec (1998, bottom panel), fitted to data generated in the attentional Drift Diffusion Model, with varying levels of attentional bias to the safe option. The color gradient represents the proportion of time spent attending to the safe option relative to the risky option in the generative process. Darker colors represent a greater attentional bias to the safe option. As can be seen, a greater attentional bias to the safe option (darker colors) is reflected in a less elevated and more extremely curved weighting function, indicating a greater underweighting of probabilities. Conventionally such weighting functions would be interpreted as reflecting pessimism. A greater attentional bias to the risky option (brighter colors) is reflected in a more elevated and more extremely curved weighting function, indicating a greater overweighting of probabilities. Conventionally such weighting functions would be interpreted as reflecting optimism. To achieve the similar shapes (more or less elevated and more or less extremely curved, right panel), which allow to accommodate particular attentional biases, the two weighting functions need to assume different parameter settings (left panel). This is due to the different functional definition of both weighting functions.

to distort the valuation of risky options, also limits its ability to reflect option-specific attentional biases.

Tversky and Kahneman (1992) weighting function Finally, we expected the weighting function used by Tversky and Kahneman (1992) to be sensitive to attentional biases to the safe over the risky option, but insensitive to attentional biases to the risky over the safe option. Indeed, the parameter estimates (cf. bottom panel in Figure 5.7) show that the curvature γ invariably approaches 1 for any generative process that is biased towards the risky option: As predicted, this weighting function is insensitive to attentional biases to the risky option, because it lacks the flexibility to make risky options appear more attractive. By contrast, moderate attentional biases towards the safe option over the risky option are accommodated in terms of increasing

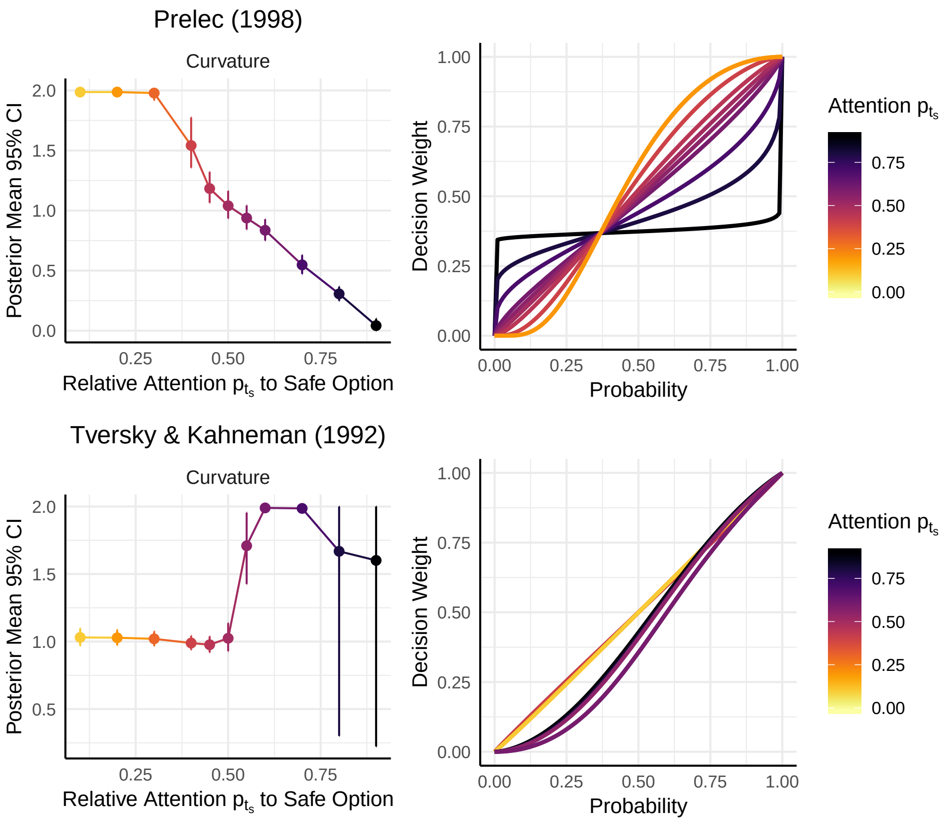

Figure 5.7: Parameter estimates and weighting functions for the one-parameter variant of the weighting function by Prelec (1998, top panel) and the one-parameter weighting function by Tversky & Kahneman (1992), fitted to data generated in the attentional Drift Diffusion Model, with varying levels of attentional bias to the safe option. The color gradient represents the proportion of time spent attending to the safe option relative to the risky option in the generative process. Darker colors represent a greater attentional bias to the safe option. As can be seen, a greater attentional bias to the safe option (darker colors) is reflected in a more extremely curved weighting functions. Conventionally, such weighting functions would be interpreted as reflecting low probability sensitivity. A greater attentional bias to the risky option (brighter colors) is reflected a more extreme curvature in the weighting function by Prelec (1998), but can not be accommodated in the weighting function by Kahneman & Tversky (1992), due to its limited flexibility for overweighting probabilities.

values of the curvature parameter γ. However, γ quickly approaches its upper bound, and for extreme attentional biases towards the safe option, the posterior intervals on the estimates become extremely wide. This indicates that it is difficult to identify a unique, suitable value of γ to accommodate strong attentional biases towards the safe option. This may be due to the fact that safe options appear more attractive under Tversky and Kahneman's weighting function as soon as γ deviates from 1—regardless in which direction. Hence biases to the safe option could in principle be accommodated either by values of $\gamma < 1$ and $\gamma > 1$, making the estimation problem difficult to solve. Overall, this inflexible one-parameter weighting function can only reflect moderate biases towards the safe option and is entirely insensitive to attentional biases to the risky option.

How CPT's Weighting Function Reflects Response Times

So far we have focused on how CPT's weighting function reflects the choice patterns generated in the aDDM. However, the aDDM does not only generate choices but also RTs. As shown previously, biased diffusion processes result in faster RTs compared to unbiased ones (but at the cost of lower

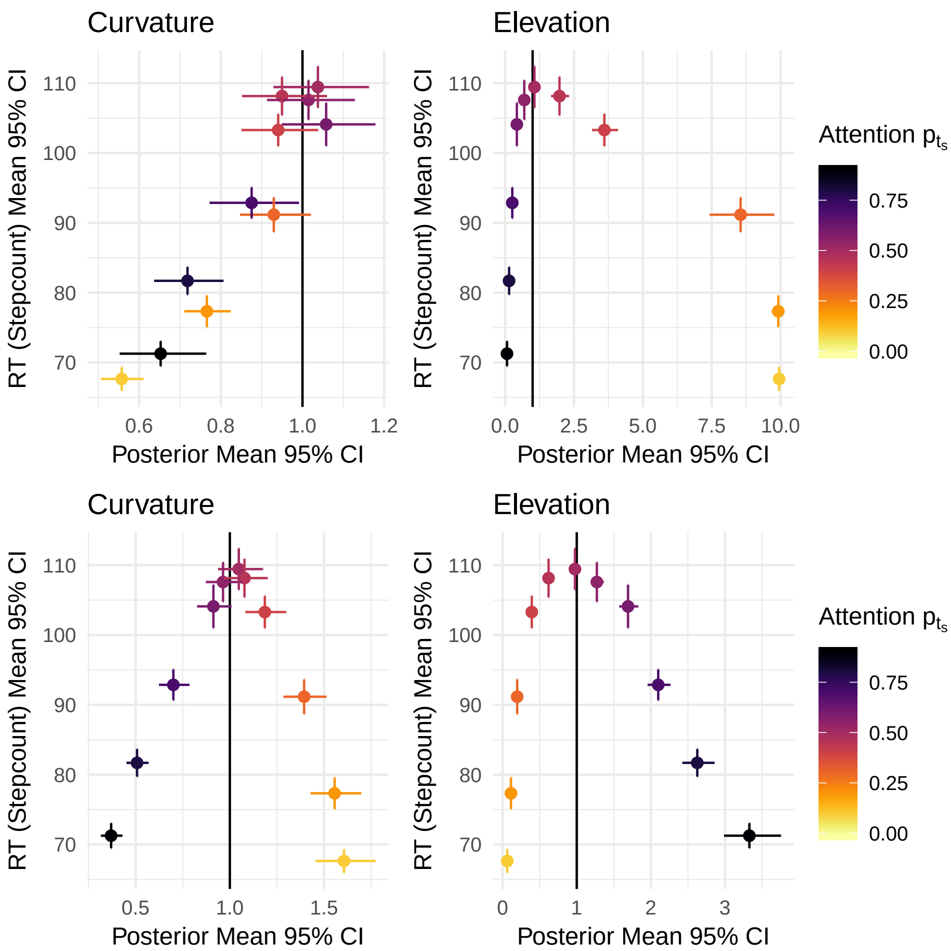

Figure 5.8: Association between RTs generated in the aDDM and parameter estimates for the probability-weighting function by Goldstein & Einhorn (1987, upper panel) and the two-parameter probability-weighting function by Prelec (1998, lower panel). The color gradient represents the proportion of time spent attending to the safe option relative to the risky option in the generative process. Darker colors represent a stronger attentional bias to the safe option.

decision quality and risk neutrality). Since the choice patterns that produce systematic signatures in the weighting function parameters also map directly onto these RT patterns, there should also be a systematic link between the parameters of CPT's weighting function and RTs. Figure 5.8 and 5.9 display the mean RTs for each level of attentional bias against the posterior mean parameter estimates for each of the four weighting functions. In the two-parameter weighting function by Goldstein and Einhorn (1987, upper panel of Figure 5.8) the highest RTs are linked to parameter estimates for both γ and δ approximating 1—both characteristics of a neutral, linear weighting function. Lower RTs are associated with lower values on γ and more extreme values on δ—both indicating a stronger distortion of probabilities. A similar pattern emerges for the two-parameter weighting function by Prelec (1998, bottom panel of Figure 5.8): The highest RTs are associated with a linear weighting function, with γ and δ approximating 1. Lower RTs are associated with deviations from neutral weighting on both parameters. That is, in both two-parameter weighting functions, linear probability weighting—and thus maximizing behavior—is associated with most time invested in the process of preference formation, and increasingly extreme distortions in probability weighting are associated with faster RTs.

The same pattern holds for the one-parameter variant of the weighting function by Pr-

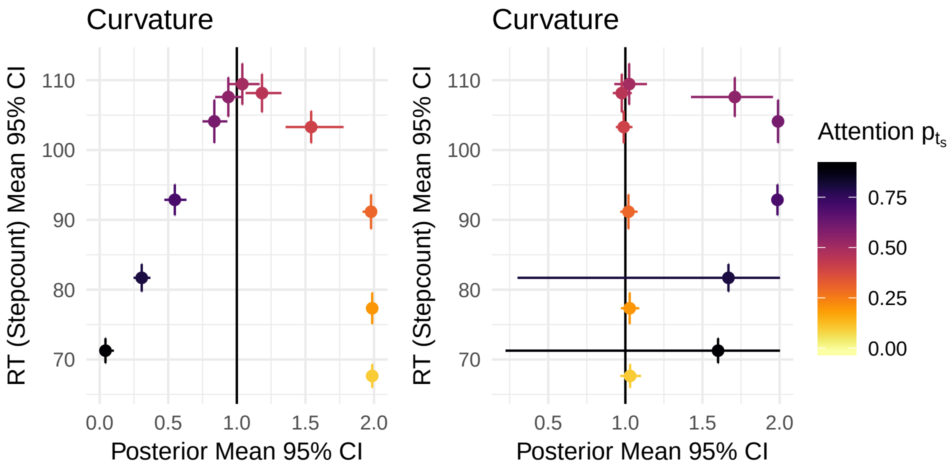

Figure 5.9: Association between response times (RTs) generated in the aDDM and parameter estimates for the one-parameter variant of the probability-weighting function by Prelec (1998, left panel) and the probability-weighting function by Tversky and Kahneman (1992, right panel). The color gradient represents the proportion of time spent attending to the safe option relative to the risky option in the generative process. Darker colors represent a stronger attentional bias to the safe option.

elec (1998, left panel of Figure 5.9), regarding the curvature parameter γ: The slowest RTs are associated with values of γ close to 1, that is, linear weighting, and faster RTs are associated with increasingly extreme probability distortions. However, at the upper bound of the parameter range, γ does no longer differentiate between the decreasing RTs—mirroring the incapacity of the one-parameter variant of this weighting function to differentiate between extreme biases towards the risky option on the choice level. Finally, in the weighting function by Tversky and Kahneman (1992), the association between RTs and γ largely breaks down (right panel of Figure 5.9), also mirroring this weighting functions' limited capacity to reflect attentional biases on the choice level.

Taken together, the behavioral consequences of attentional biases in the aDDM—including both choice behavior and response times—have systematic signatures in CPT's weighting function. Across all weighting functions, more linear (objective) probability weighting—and thus maximizing behavior—was associated with the slowest RTs, resulting from unbiased or barely biased diffusion processes. Faster RTs, resulting from biased diffusion processes that deviate from maximization, are associated with pronounced distortions in probability weighting. That is, although CPT alone makes no predictions about RTs, the connection to aDDM reveals that CPT's probability weighting function can reflect speed-accuracy trade-offs.

Did Other Parameters Reflect Attentional Biases?

So far we have focused exclusively on CPT's probability-weighting function, since we had theoretically motivated predictions about its capacity to account for attentional biases. However, the fitted CPT models also included a value function with a free parameter for outcome sensitivity, complemented by a logit choice rule with a free parameter for response noise (also referred to as choice sensitivity). We next examine whether attention also systematically affected the estimates for outcome sensitivity and response noise, although we had no directed hypotheses about these parameters. The results are displayed in Figure 5.10.

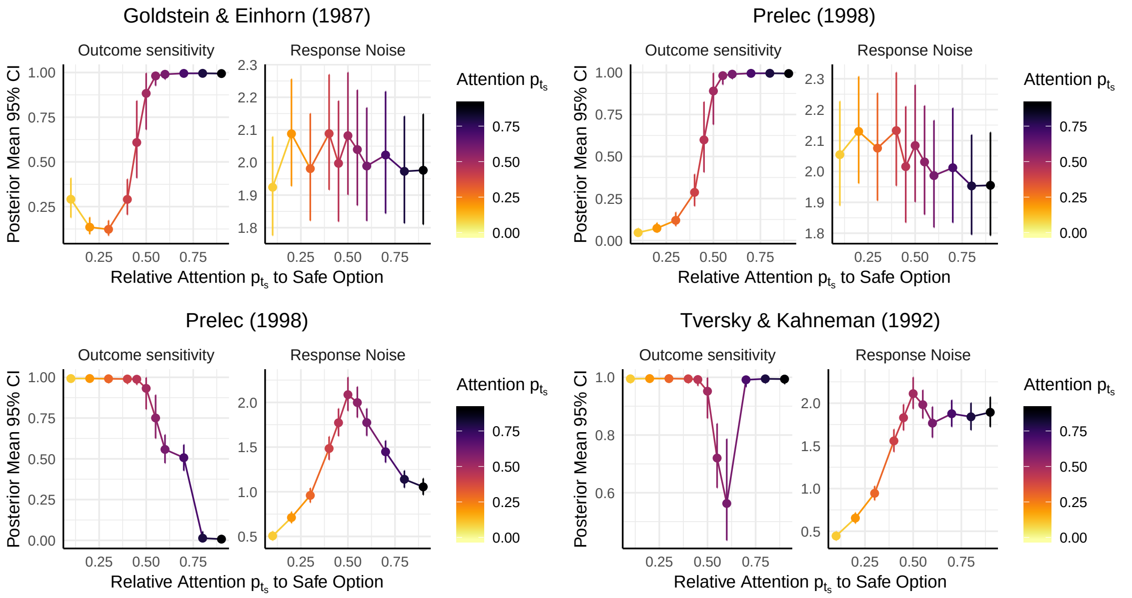

Figure 5.10: Impact of p_{t_s} on the other CPT parameters when using the weighting function by Goldstein and Einhorn (1987, top row, left panel), the two-parametric variant of the weighting function by Prelec (1998, top row, right panel), the one-parametric variant of the weighting function by Prelec (1998, bottom row, left panel) or the one-parametric weighting function by Tversky and Kahneman (1992, bottom row, right panel).

Value function

In CPT with the two-parametric weighting functions by Goldstein and Einhorn (1987) and Prelec (1998), increasing attentional biases were linked to an increase in outcome sensitivity (see top row in Figure 5.10). In CPT with Prelec's (1998) one-parametric weighting function, the direction of this effect was reversed, and in CPT with Tversky & Kahneman's (1992) weighting function, outcome sensitivity was mostly high, except for one sudden, unsystematic drop at mid-range attentional biases (see bottom row in Figure 5.10). That is, viewed across all four implementations of CPT, the attentional biases had considerably less systematic effects on outcome sensitivity than on probability weighting.

Why is this the case? Probabilities in risky choice problems are bounded between 0 and 1 and need to add up to unity within each option. Hence, in a choice between a safe option and a two-outcome risky option, a single probability of the risky option is sufficient to fully describe *all* probabilities. Consequently, how specific shapes of the weighting function distort the attractiveness of risky and safe options can be relatively easily predicted (cf. Appendix D.4). This clear and general association underlies the highly systematic effects of attentional biases on probability weighting. By contrast, safe and risky outcomes are not in principle bound to a particular range, and the magnitude of one outcome does not imply the magnitude of other outcomes. The outcomes of safe options are not in principle fixed, in contrast to their probabilities. Consequently, the association between the (barely constrained) possible outcomes constituting safe and risky options, the shape of the value function, and the relative attractiveness of the options, cannot be predicted in the same general, systematic manner as the respective association for the probabilities. This explains why attentional biases had considerably less systematic effects on the outcome sensitivity parameter than on the probability weighting parameters. However, it may be possible to carefully construct a set of choice problems where the outcomes are configured in such a way that attentional biases are also reflected more systematically in the outcome sensitivity parameter.

Choice rule

Did attentional biases systematically affect the response noise parameter of the choice rule? In CPT with the two-parametric weighting functions by Goldstein and Einhorn (1987) and Prelec (1998), the response noise parameter was not systematically affected by attentional bias (see top row in Figure 5.10). In CPT with Prelec's less flexible one-parametric weighting function, response noise increases (indicated by a decreasing ρ parameter) with more extreme attentional biases: The behavioral consequences of stronger attentional biases, which could not be accounted for sufficiently by the inflexible probability-weighting function, are attributed to noise. A similar effect is observed in CPT with Tversky and Kahneman's weighting function, where especially attentional biases to the risky option (which cannot be accounted for by this inflexible weighting function) are associated with higher response noise (see bottom row in Figure 5.10).

5.2.4 Extension to Choices Between Risky Options and to the Loss Domain

Choices between two risky options

We have developed and illustrated our argument in choices between safe and risky options. Does the mapping between attentional biases in aDDM and weighting functions in CPT extend to choices between two risky options? Indeed, it does—as long as the risky options differ in their probabilities. In choices between two risky options, the attentional bias in the aDDM is no longer defined as the relative attention to the safe option, but as the relative attention to the option with the larger probability p_{high} of the highest outcome. A stronger attentional bias towards this option is reflected in a less elevated and a more strongly S-shaped weighting function—because under such a weighting function higher probabilities will be overweighted more (or at least underweighted less) than lower probabilities. To illustrate this, we conducted a cross-theory recovery study like the one presented here for choices between two risky options, presented in detail in Appendix D.2.

Choices between losses

All choice problems in our choice set involved outcomes from the domain of gains. Can the results be generalized to the domain of losses? When using the aDDM to generate choices the domain of losses, the effects of attention on preferences reverse, relative to the domain of gains. For instance, paying more attention to a safe loss amplifies the accumulation of negative evidence regarding this safe loss, making it appear less attractive and less likely to be chosen. Nevertheless, the effects of attention on the weighting functions are identical across domains. That the same weighting function can account for opposite behavioral patterns in the the domain of gains and losses can be illustrated by the certainty effect. Both the tendency to choose safe gains and to reject safe losses are accounted for by an inverse S-shaped weighting function, which overweights (positive and negative) safe outcomes. Hence, identical weighting functions can also account for opposite behavioral consequences of attentional biases in the domains of gains and losses.

5.3 Empirical Analyses: Do Attentional Biases in Decision from Experience Affect Probability Weighting in CPT?

So far, we have made a purely theoretical argument: Attentional biases, implemented in the aDDM, have highly systematic signatures in CPT's probability-weighting function. Do option-specific at-

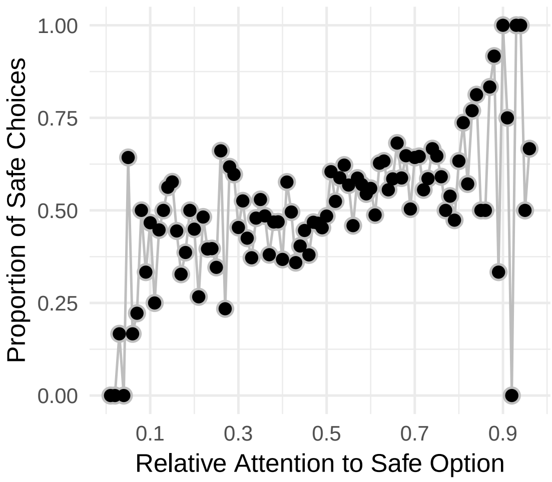

Figure 5.11: Empirical risk preference as a function of the attentional bias to the safe option (measured as proportion of samples from the safe option) in the sampling paradigm for DfE. As in the simulation analysis, a greater attentional bias to the safe option was associated with a higher propensity to choose this safe option. The same holds for risky options.

tentional biases also affect empirically observed probability weighting? We test this question using data from the sampling paradigm for decisions from experience (cf. Hertwig & Erev, 2009). In the sampling paradigm, participants can explore initially unknown payoff distributions by repeatedly sampling their outcomes for as long as they like before making a final, consequential choice. The sampling paradigm allows for a straightforward measurement of option-specific attentional biases—the proportion of samples drawn from each option on each trial. We test whether such option-specific attentional biases in the sampling paradigm have systematic signatures in CPT's weighting function parameters, analogue to the patterns identified by simulation.

We used data from the sampling paradigm in decision from experience compiled in the context of the meta-analysis on the description-experience gap by Wulff et al. (2018). To ensure comparability with our simulation results, we analyzed trials from the domain of gains where one option was experienced as safe, while the other option was experienced as risky with two distinct experienced outcomes.[9] For a trial to be included in the analysis, both the safe and the risky option had to be sampled at least once. In total, we analyzed data from 1,994 participants and 7,573 sampling sequences and choices. For each trial, we computed the experienced probability of each option's individual outcomes, and the proportion of samples from the safe option in reference to the total number of samples on each trial, as a measure of attentional bias towards the safe option.

Figure 5.11 depicts the proportion of choices of the safe option as a function of the attentional bias to the safe option. More pronounced biases towards the safe option are associated with a higher propensity to choose this option, and the same holds for risky options. To statistically corroborate this effect, we estimated a Bayesian mixed-effect logistic regression in the rstanarm package in R (Goodrich et al., 2018), using the choice of the safe option as the dependent variable. The model included a fixed effect for the proportion of samples from the safe option, and random intercepts for each participant and study from the meta-analysis. There was a credible effect of the magnitude of sampling biases to the safe option on the tendency to choose this safe option ($\beta = 1.18$, 95% CI $[0.8, 1.57]$). That is, empirical risk attitudes are linked to option-specific atten-

[9] In the context of the empirical analysis we refer to "safe" options meaning options that were *experienced* as safe—which also includes options whose underlying distribution offered several probabilistic outcomes, but only one of these outcomes was encountered during sampling.

tional biases in the sampling paradigm. Is this association between attentional biases and choice behavior also reflected in CPT's weighting function?

5.3.1 How CPT's Weighting Function Reflects Empirical Option-Specific Sampling Biases

The empirical data was modelled in two variants of hierarchical Bayesian CPT, using the two-parameter weighting functions by Goldstein and Einhorn (1987) and by Prelec (1998). The probability-weighting functions were estimated based on the experienced probabilities, such that deviations from linear weighting cannot be attributed to the under- or oversampling of outcomes relative to their objective probability—a prevalent regularity especially when overall sample sizes are small (Hertwig & Erev, 2009). To measure the potential link between attentional biases and CPT's weighting function, the elevation and curvature parameters could co-vary with the relative attention to the safe option on each trial. It is important to emphasize that the model does not imply but merely measure this potential association between attentional biases and weighting function parameters—much like a linear regression model would. If the data does not provide evidence for such an association, it will not show up in the parameter estimates. Details on the CPT models are provided in Appendix D.3.

Goldstein and Einhorn (1987) weighting function

How does the weighting function by Goldstein and Einhorn (1987) reflect empirical attentional biases to the safe option in sampling paradigm? The top panel in Figure 5.12 shows the mean posterior weighting function parameter estimates as a function of sampling bias, as well as the resulting weighting functions. As can be seen, there is a clear association between the attentional bias in sampling and the weighting function parameters. This association is strikingly similar to the results of our simulation analyses. Specifically, δ decreases with an increasing proportion of samples from the safe option, indicating a less elevated weighting function. Biases towards the risky option are reflected in $\delta > 1$ and biases towards the safe option are reflected in $\delta < 1$. Moreover, increasingly extreme attentional biases (whether in favor of the safe or the risky option) are reflected in lower values of γ, indicating a more extreme curvature. For unbiased sampling, the elevation and curvature parameters are close to 1, that is, linear probability weighting. These empirical results closely resemble our findings based on synthetic data generated in the aDDM.

Prelec (1998) weighting function

The empirical attentional bias is also systematically linked to the shape of the two-parameter weighting function by Prelec (1998). The bottom panel in Figure 5.12 shows the mean posterior estimates of the weighting function parameters for each level of attentional bias in the empirical data, as well as the resulting weighting functions. The parameter δ increases with an increasing proportion of samples from the safe option, relative to the risky option, indicating a lower elevation. Moreover, increasing attentional biases to the safe option are reflected in lower values of γ. Therefore, the weighting function is more convex (or inverse S-shaped) under stronger sampling biases towards the safe option, and more concave (or S-shaped) under stronger sampling biases towards the risky option. Unbiased sampling is reflected in linear probability weighting (i.e., γ and δ of approximately 1). These empirical results closely resemble our findings based on synthetic data generated in the aDDM.

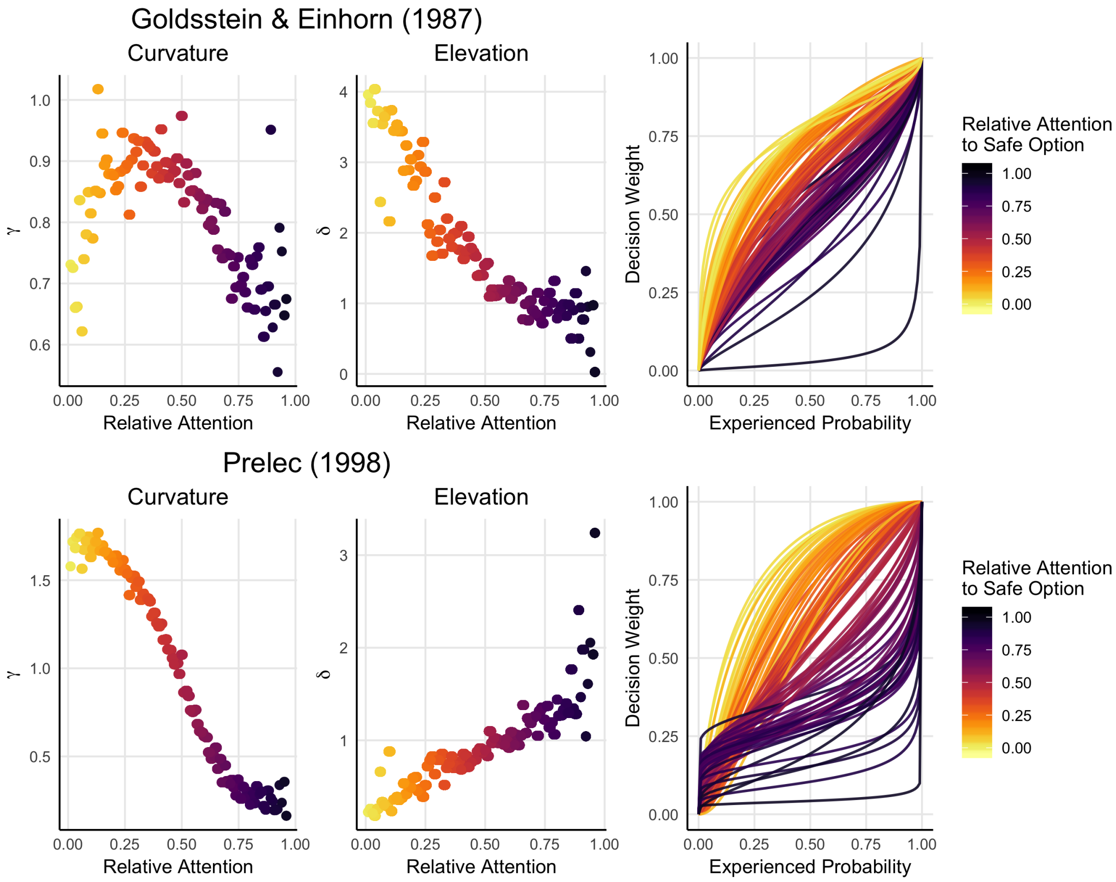

Figure 5.12: Attentional biases in empirical sampling sequences in decision from experience are linked to probability weighting in CPT. The color gradient represents the attentional bias, measured as the proportion of samples from the safe option in each trial. Darker colors represent a greater attentional bias to the safe option. Left panel: Mean parameter estimates for the curvature and elevation parameters of the weighting functions by Goldstein & Einhorn (1987) and Prelec (1998), for each level of attentional bias in the empirical sampling sequences. Right panel: Resulting weighting functions for parameter estimates under each level of attentional bias. As can be seen, greater attentional biases to the safe option (darker colors) are reflected in less elevated and more extremely curved weighting functions. Conventionally such weighting functions would be interpreted as indicative of pessimism and low probability sensitivity. Greater attentional biases to the risky option (brighter colors) are reflected in more elevated and more extremely curved weighting functions. Conventionally such weighting functions would be interpreted as indicative of optimism and low probability sensitivity. Overall, the empirical patterns reproduce the results from the simulation analyses remarkably well (cf. Figure 5.6).

5.4 Discussion

We demonstrated in a cross-theory parameter recovery that the behavioral consequences of attentional biases in the aDDM, a popular model in the sequential sampling tradition, have systematic signatures in probability weighting when the resulting choices are modeled with CPT, arguably the most influential model in the neo-Bernoullian tradition of modeling risky choice. In the aDDM, option-specific attentional biases can shift the comparison between safe and risky options in favor of the option that receives more attention. To the extent that four different weighting functions in CPT can make risk options appear more or less attractive, compared to objective weighting, they can also account for option-specific attentional biases. After identifying this correspondence in simulations, we tested whether it also holds empirically, using data from decisions from experience. Indeed a link between empirical option-specific attentional biases in sampling behavior and probability weighting in CPT was found, and the patterns were very similar to those identified in the simulation. We next discuss several implications of our results, starting with psychological interpretations of the shape of the weighting function.

5.4.1 Implications for Psychological Interpretations of the Probability-Weighting Function

The parameters of CPT's probability-weighting function are conventionally interpreted in terms of distinct psychological constructs, namely probability sensitivity and optimism or pessimism (Abdellaoui et al., 2010; Gonzalez & Wu, 1999; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Our results suggest an alternative interpretation in terms of attentional processes. Specifically, distinct shapes of the weighting function may reflect basic—and even observable—features of information acquisition and processing: The existence, direction, and severity of option-specific attentional biases. This may have far-reaching consequences.

The notion of probability sensitivity

In their seminal article on prospect theory, Kahneman and Tversky (1979, p. 280) emphasized that "decision weights measure the impact of events on the desirability of prospects, and not merely the perceived likelihood of these events". This conceptual distinction between decision weights and subjective probabilities is accentuated by our finding that probability-weighting functions can closely trace the dynamics of a data-generating mechanism in which probabilities are not even explicitly represented: In sequential sampling models like the aDDM, probabilities only affect evidence accumulation indirectly, by determining the relative frequency with which the outcomes are sampled. That is, probabilities are inherent in the structure of the world, but only the sampled outcomes themselves, not their probabilities, are explicitly represented in the model as evidence for evaluating options.

This challenges the common psychological interpretation of the curvature parameter in terms of diminishing sensitivity to probabilities (Gonzalez & Wu, 1999): It may be problematic to use estimates of the curvature to measure the decision maker's ability to discriminate probabilities, given that this parameter can vary very systematically in the absence of any explicit representation of probabilities. Caution is demanded especially when interpreting empirical data, where true representations cannot be directly accessed (by contrast to simulations). This notion is consistent with an argument by Sanborn and Chater (2016), who posit that brains are poorly adapted to represent or calculate probabilities, and more likely implement probabilistic reasoning based on a sampling-based mechanism without explicitly represented probabilities.

The notion of optimism and pessimism

Since the seminal paper by Gonzalez and Wu (1999), many studies have used the elevation of CPT's weighting function trying to measure individual differences in motivational constructs such as optimism and pessimism (e.g. Abdellaoui et al., 2010; Booij et al., 2010; Charupat et al., 2013; Etchart-Vincent, 2004; Fehr-Duda et al., 2006; Vieider et al., 2015).[10] Yet, our findings suggest an alternative interpretation for the elevation parameter. We show that the elevation can be shifted around systematically from trial to trial by modulating option-specific attentional biases.

[10] The paper by Gonzalez and Wu (1999) has been cited 1264 times (cf. google scholar, 17.04.2019), providing a rough sense of the vast impact of the authors' central claims about the psychological interpretability of CPT's weighting function.

Notably, empirical attentional biases are often guided by superficial features of information (Orquin & Loose, 2013; Orquin et al., 2018), which may arbitrarily vary from situation to situation. Hence, even if CPT's elevation parameter reflects *both* attentional biases and optimism/pessimism, such fluctuations in attention would likely render the measurement of optimism and pessimism quite imprecise. On the other hand, people might also have stable individual dispositions for attending to specific types or features of stimuli. In this light, the considerable intra-individual stability in the elevation parameter across experimental sessions (cf. Glöckner & Pachur, 2012; Pachur et al., 2018) might reflect such personal attentional predispositions. Hence, further empirical research using process tracing will be necessary to separate attentional components (both temporally fluctuating and stable within persons) of the elevation parameter from non-attentional components, reflecting psychometric constructs such as optimism and pessimism. This may help to evaluate whether, to which degree, and in which cases the conventional interpretation of CPT's elevation parameter in terms of optimism or pessimism is still warranted.

5.4.2 Attention-Based Explanations for Empirical Phenomena with Characteristic Weighting Functions

Our results also offer novel, process-based explanations for key phenomena of risky choice, such as the certainty effect, the fourfold pattern, and the description-experience gap. These phenomena have predominantly been discussed in the neo-Bernoullian terms of probability weighting, but our findings may contribute to a more process-oriented understanding thereof.

The certainty effect

The certainty effect describes a preference for safe over higher valued risky options, which reverses when the safe option is replaced by another risky option (Kahneman & Tversky, 1979; Tversky & Kahneman, 1986). This apparent overweighting of safe over probabilistic events is typically captured by an inverse S-shaped weighting function in CPT. Our results suggest a new, process-based explanation for the certainty effect: Inverse S-shaped weighting functions in choices between safe and risky options may reflect attentional biases towards safe options, which shift the comparison between the options in favor of the safe option.

Indeed, in a recent eye-tracking study Zilker and Pachur (2019, see chapter 4) participants displayed pronounced attentional biases towards safe options over risky options when safe options were described using fewer pieces of information than risky options. Presenting safe options in a more complex format counteracted the attentional biases, and also reduced the proportion of safe choices. Hence, attentional biases towards simple safe options in standard risky choice tasks may underlie the apparent overweighting of certainty when modeling the data in CPT. Further substantiating this idea, attention was allocated more symmetrically in choices between two risky options, which are structurally more similar than safe and risky options (Zilker & Pachur, 2019). Likewise, weighting functions in choices between two risky options tend to be more linear than those in choices between safe and risky options (Glöckner et al., 2016).

The fourfold pattern

The fourfold pattern of risk attitudes describes risk aversion for gains and risk seeking for losses of high probability, accompanied by risk seeking for gains and risk aversion for losses of low probability (Tversky & Fox, 1995; Tversky & Kahneman, 1992). This pattern can be accommodated by assuming an inverse S-shaped weighting function in CPT, implying that small probabilities are overweighted and moderate to large probabilities underweighted. The fourfold pattern is typically demonstrated in choices between safe and risky options. Hence, to the extent that safe options attract more attention, the inverse S-shaped weighting functions may again—as in the case of the certainty effect—be a consequence of systematic attentional biases.

The description-experience gap

Decisions from description and decisions from experience seem to evoke distinct probability weighting patterns—an apparent overweighting (description) and underweighting (experience) of rare events (cf. Wulff et al., 2018). Common operationalizations of the description-experience gap are even based on assuming these probability weighting patterns. For instance, the discrete operationalization of the gap posits that the gap is present if the rare event received more weight in description than in experience, that is, if the weighting function is more inverse S-shaped (or less S-shaped) in description than in experience. In the light of our results, these distinct weighting function signatures may be due to opposite option-specific attentional biases. Specifically, participants may predominantly attend to the safe option in description and predominantly sample the risky option in experience. This is supported by the previously described findings from the eye-tracking study on decision from description by Zilker and Pachur (2019), and by the finding that people tend to search more variable (risky) options more than safe options in decision from experience (Lejarraga et al., 2012; Pachur & Scheibehenne, 2012). These opposite attentional biases may entail differences in choice behavior which get picked up by common operationalizations of the gap. This novel explanation for the description-experience gap will be tested thoroughly in future work.

5.4.3 Different Paths to Theory Integration

As outlined in the introduction, psychology is sometimes viewed as widely lacking overarching theoretical frameworks (Gigerenzer, 2010), and this may have fostered the replication crisis (Muthukrishna & Henrich, 2019). Without doubt, substantive integrative progress will be necessary to arrive at a more holistic, theoretically grounded understanding of the human psyche—or at least to unify different phenomena within specific sub-disciplines, such as decision making. In this light, one of the most important contributions of the work presented here is to strengthen the ties between two largely disjoint streaks of formal decision theory—neo-Bernoullian and sequential sampling models. Some previous steps to bridge this divide have been taken, broadly following two general approaches to theory integration. To put our own work into context, we illustrate these approaches by reference to this previous work, and highlight their respective merits and shortcomings.

Hybrid models

The first approach for theory integration involves the construction of new, hybrid theories that capitalize on insights and constructs from both the neo-Bernoullian and the sequential sampling world. Such hybrid models exist along a spectrum: Some incorporate only few details from the "opposite" framework, and others offer a genuinely integrative mixture of ideas and constructs. For instance, the transfer-of-attention-exchange model (TAX, Birnbaum, 1999) is firmly rooted in the neo-Bernoullian tradition, but explicitly assumes that the over- or underweighting of probabilistic events reflects their competition for limited attentional resources. Attentional weight is transferred along the ordered branches (possible events). Regardless of this (verbal) attentional interpretation, TAX does not incorporate any formal features (e.g., a sampling processes) which originate outside of the neo-Bernoullian world.

On the other hand, Decision Field Theory (DFT, Busemeyer & Townsend, 1993), was developed by extending and refining the assumptions of static utility models to dynamic and probabilistic contexts. DFT can be described as a sequential sampling model whose assumptions heavily depend on considerations originating in neo-Bernoullian theory. Among the hybrid models discussed here, DFT may therefore be the most genuinely integrative one. Under this integrative perspective, the authors also offer a psychological interpretation of the weights in subjective expected utility (SEU), as reflecting the amount of attention given to each event—which closely resembles our own insights with respect to CPT.

Besides models themselves, experimental paradigms are often direct reflections of the ways in which traditions tend to think about particular problems, constraining the very nature of data that even gets generated and considered (Gigerenzer, 2010). Our final example for hybrid modeling illustrates how this gap between behavioral phenomena, which are predominantly considered within their native framework, can be bridged. Diederich and Trueblood (2018) transplanted constructs from two neo-Bernoullian theories (SEU and CPT) into a sequential sampling model. They applied the resulting model to capture the impact of time pressure, a factor classically discussed within the process-oriented tradition, on framing effects, a phenomenon rooted in the neo-Bernoullian world. Hence, they transcend the conventional bounds between the neo-Bernoullian and the process-oriented world not only on the level of theory, but also on the level of application.

These examples illustrate some merits of hybrid modeling for theory integration. Nevertheless, since hybrid modeling involves the construction of new theories, the genuinely unifying power of this approach may be questioned.

Cross-theory parameter recovery

A second approach for theory integration aims to learn more about one set of theoretical constructs by viewing them through the lens of a different theory. Our cross-theory parameter recovery between aDDM and CPT belongs to this category. Similarly, Pachur et al. (2017) demonstrated that heuristic strategies have quite distinct signatures in terms of CPT parameters. Moreover, Luan et al. (2011) used the language of signal detection theory to better understand fast and frugal trees (FFT).

In all these examples one set of constructs is used to model behavior that is known to be generated by a different theory. If both theories are fully disjoint, meaning that their constructs share no explanatory power, this procedure should result in entirely unsystematic parameter estimates. However, theories that are successful within their native realm (which are natural candidates for integration) typically capture essential aspects of behavior, which may to some extent overlap with the essential aspects identified by influential theories in other traditions—such as systematic deviations from maximization. Cross-theory parameter recovery makes this shared essence of disconnected theoretical positions graspable, and provides a common language for researchers to communicate about ideas.

Moreover, the cross-theory recovery approach highlights how different theoretical positions can complement each other. For instance, CPT in itself does not predict RTs, but the association with aDDM unlocks RTs as a new territory for CPT-based enquiry. Another benefit of this approach is exemplified by our discovery that CPT's weighting function can closely trace attentional biases—without any refinement to CPT's original assumptions. This demonstrates that it may not be necessary to invent or introduce new constructs to transcend the explanatory scope originally attributed to one particular theory. Rather, connections to other frameworks can reveal previously overlooked capacities of constructs that are already established as part of a theory.

5.4.4 An Extension to Other Attentional Sequential Sampling Models?

The aDDM is not the only sequential sampling model that incorporates attentional processes. For instance, Decision Field Theory (DFT, Busemeyer & Townsend, 1993) and by extension, Multi-alternative Decision Field Theory (MDFT, Roe et al., 2001), the Leaky Competing Accumulator (LCA, Usher & McClelland, 2001, 2004), and the Multiattribute Linear Ballistic Accumulator (MLBA, Trueblood et al., 2014), also build on the sequential sampling framework to formalize time-consuming deliberation processes that consist of a continual evaluation of alternative options, to some extent, weighted by attentional constructs.

What can be said about a possible correspondence between attentional constructs in these models and CPT's weighting function, based on our results? Broadly speaking, it seems conceivable that CPT's probability-weighting function may be linked to constructs capturing attentional weighting in these other models in a similar way as to the attentional weighting in the aDDM. However, without conducting a concrete simulation analysis like the one presented here, such extrapolations remain quite speculative. This is because the aDDM differs from other attentional sequential sampling models in some important assumptions, especially regarding the conceptualization of attention. Some of these distinctions are fleshed out below.

Attribute- or option-specific attention

The first distinguishing characteristic is whether attention is thought to be allocated to individual attributes or entire options. In DFT, MDFT, and LCA attention is assumed to sequentially scan individual attribute dimensions rather than entire options, as in the aDDM. This difference in the resolution of attention allocation may entail subtle differences in choice patterns, which may in turn translate into different probability weighting signatures when modeled in CPT.

Measuring or modeling attention

The second distinguishing characteristic is whether attention allocation is measured or modeled. The aDDM takes observed attentional patterns—for instance, quantified via eye tracking—as inputs to the model. By contrast, in DFT and MDFT the switching of attention itself is modeled as a Bernoulli process (which can be imagined as the repeated flipping of a—potentially biased—coin). In LCA, shifts in attention follow a fixed probability. In MLBA, option-specific attentional weights are defined as a function of the discriminability of attributes, and do not add up to 1. That is, although these weights are conceptualized as capturing attentional processes, they are not probabilities, and hence do not precisely quantify the distribution of attention (Trueblood et al., 2014). Since these formal approaches to capturing attentional processes differ quite fundamentally, attentional weights in different models may not necessarily translate into the same choice regularities, and by extension, probability weighting signatures in CPT.

Competition among options

Another distinguishing characteristic of different attentional sequential sampling models is if and how they implement competition among the options for evidence. The aDDM's assumption of a relative evidence threshold implies that incoming evidence always moves the (single) accumulator closer to one option's boundary and thereby, at the same time, away from the alternative option's boundary. Since this constant comparison of options in the aDDM achieves competition among options, evidence in favor of one option does not need to explicitly discount or inhibit evidence accumulated in favor of the alternative. Other models that assume several racing accumulators, and absolute rather than relative evidence thresholds, implement competition among options via lateral inhibition. MDFT assumes lateral inhibition of valences between the options, determined by their distance in the attribute space. In LCA, activations can also inhibit each other, but independently of their distance. (M)DFT and LCA further assume memory related decay over time via self-connections of options to their previous activation states, a feature not present in the aDDM. These different assumptions regarding competition and temporal decay may entail crucial differences in choice behavior, which may, again, be reflected in different parametric signatures if modeled in CPT.

Due to these and other divergent assumptions between the aDDM and other attentional sequential sampling models, simply extrapolating from our results to an analogue correspondences between attentional construct in other models and CPT's weighting function would likely involve unwarranted generalizations, and not do justice the subtle originality of each model's behavior. Thus, we refrain from such speculation. However, whether the correspondence can be extended may be addressed by conducting further cross-theory recovery analyses, including more than just the two exemplary models addressed here. Our analysis may only mark the starting point for further enquiry into this kind of theory integration.

5.4.5 Conclusion

Formal frameworks equip scientists with a roadmap for reasoning in a theoretically grounded manner, provide them with a shared language, and enable them to make quantifiable predictions. Both the neo-Bernoullian and the sequential sampling framework have facilitated and shaped scientific progress within their respective disciplines in this manner. However, formal theories are necessarily abstractions and cannot provide comprehensive accounts of phenomena themselves in all their richness. As such, they operate on a specific, closely circumscribed conceptual level, such as the level of attentional processes (aDDM), or the level of apparent attribute distortions (CPT). Our simulation analyses trace out a previously overlooked correspondences between these levels. The results demonstrate that even constructs that seem to have very little to do with each other superficially, such as attentional biases and probability distortions, may still relate to remarkably similar structures in data. The concrete usefulness of overlaying different frameworks in this way is illustrated in our empirical analysis, which makes a substantive contribution: Previously neglected option-specific biases in attention can help to explain risky choice behavior and characteristic probability weighting patterns in decision from experience. That is, theory integration can open up innovative perspectives on empirical phenomena that have been studied in great detail in their native tradition.

5.5 Author Contributions

Conceptualization and Methodology: V.Z.; Simulations, Data Analysis and Modeling: V.Z.; Empirical Analysis: V.Z.; Writing—Original Draft: V.Z.; Writing—Reviewing & Editing: V.Z. and T.P.

5.6 Data and Code Availability

Code to implement all analyses is hosted at https://osf.io/e7xtr/?view_only=91d9160b279749978db3e8f38a014ad4. Data for the empirical analyses is hosted by Dirk Wulff at https://www.dirkwulff.org/data/WulffEtAl_TwoModes_Data.zip.

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6 | Synthesis

In this chapter I carve out the major contributions and implications of my work and embed them in the broader discussions they contribute to.

6.1 Major Empirical Contributions

In the empirical parts of this dissertation, I demonstrated why it can be so difficult to predict behavior in risky choice tasks reliably, focusing on choices between described lotteries. I investigated how risky choice behavior depends on features of stimulus materials besides risk itself—namely option complexity—and on individual differences in psychological characteristics besides latent risk attitude—namely attentional processes. Interactions between these factors were illustrated by comparing younger and older adults.

6.1.1 Option Complexity Modulates Risky Choice Behavior

I showed that risky choice behavior in choice problems with positive, non-zero outcomes can be quite easily pushed around by manipulating differences in option complexity between the options in the choice problem. People, and especially older adults, tend to choose safe and risky gains less when they are presented in a more complex format (while keeping the complexity of the alternative option constant). This research stands in the tradition of classical investigations of preference construction, which often focused on the anatomy of the environment—for instance, demonstrating preference reversals due to changing stimulus features (e.g., Binswanger, 1980; Johnson et al., 1988; Lichtenstein & Slovic, 1971). However, I also showed that environmental features tend to interact with each other—option complexity had a lesser or no impact in choice tasks involving losses and outcomes of zero—and with individual differences in psychology—choice behavior was more sensitive to option complexity in older than in younger adults. Hence, to fully understand if and when a particular confound matters (and should be taken into account for predicting choice behavior), one needs to also consider *how* it exerts its confounding influence on the mind of the decision maker. Although manipulating option complexity does not affect the content of information, such as the value or risk of options, it affects how this information can be and is processed—by humans in general, and by individuals with varying cognitive capacities in particular. Individual differences in information processing capacities—such as attentional capacities—are essential for understanding *how* environmental features affect the process of preference construction.

6.1.2 Age-related Changes in Selective Attention Affect the Construction of Risk Preferences

Selective processing is a staple of intelligent cognition under resource constraints. Both research on human (Dayan et al., 2000; Dempster, 1991; Heitz et al., 2005; Stankov, 1983, 1988) and artificial intelligence (Blum & Langley, 1997; Jensen & Shen, 2008) recognizes the importance of ignoring irrelevant, interfering information and of processing relevant information in a focused manner for arriving at good choices. Indeed, attentional processes come to bear in most dimensions of fluid intelligence. For instance, since working memory has limited capacity, attentional selection has the important task of prioritizing the storage to the most relevant information, and keeping out unnecessary clutter (Myers et al., 2017). Consistently, age differences in basic attentional processes seem to contribute to age-related impairments in fluid intelligence (Salthouse, 2004; Stankov, 1988), which are in turn frequently invoked to explain age differences in decision making (cf. Brocas et al., 2019; Mamerow et al., 2016; Mata et al., 2011; Mata et al., 2007; Pachur et al., 2017; Pachur et al., 2009). In younger adults, attention has also been found to directly affect preferences by prioritizing and reinforcing the impact of currently looked at information (e.g., Krajbich et al., 2012; Krajbich & Rangel, 2011; Smith & Krajbich, 2019). The neural mechanisms that implement selective attention by prioritizing the processing of relevant information from the environment are impaired in older age (cf. Gazzaley et al., 2008; Gazzaley et al., 2005). In this dissertation, I newly established a direct link between age-related deficits in selective attention, measured via computational modeling, and age differences in risk preference.

I demonstrated that preference formation in decision making under risk is profoundly shaped by age differences in selective attention. While both age groups showed attentional biases towards simple safe options, attention only amplified the impact of these options on younger, but not older adults' choice processes. My findings also highlight how cognitive capacities and the environment interact during preference construction: Increasing the complexity of safe options modulated the impact of attention on preferences in younger adults, but the non-attentional baseline preferences in older adults. Although in both age groups the construction of risk preferences is influenced by option complexity, the specific constructive processes differ dramatically. This underlines that mere risky choice behavior results from different psychological processes across individuals and variants of the choice task, and that the construction of risk preferences can vary across the lifespan as cognitive capacities change.

6.1.3 Option-specific Sampling Biases Explain Choice Behavior in Decisions from Experience

As a side-product of investigating the mapping between attentional biases and patterns in probability-weighting, I also obtained a new explanation for choice behavior in decision from experience. In my re-analysis of data from the meta-analysis on the description-experience gap by Wulff et al. (2018), I show that option-specific biases in sampling behavior are systematically linked to risky choice behavior: Predominantly sampling the more (less) risky option in the choice set is associated with a greater propensity for choosing this option. This is analogous to the finding in decision from description that people tend to choose safe options more when they look at them for a greater proportion of time. Hence, I identified a common denominator of behavior in decision from description and experience—option-specific biases in information search. This may reconcile some of the puzzling differences between both paradigms: Systematic attentional biases to safe options in decision from description (as identified in chapter 4), accompanied by systematic sampling biases in favor of risky options in decision from experience (Lejarraga et al., 2012; Pachur & Scheibehenne, 2012), may contribute to the opposite behavioral tendencies in both paradigms (Hertwig & Erev, 2009; Wulff et al., 2018). That is, option-specific attentional biases may help to explain the description-experience gap. This will be an exciting direction for future research.

6.1.4 Implications for the Behavioral Measurement of Risk Preferences

To draw together these empirical findings, reconsider the seeming paradox of measuring risk attitudes behaviorally: Although risk attitude can be regarded as a stable psychological trait, behavior in risky choice tasks—which try to condense the problem of decision making under risk to its essential parts—often varies considerably across measurement time-points and formats of the task (Frey et al., 2017; Pedroni et al., 2017).

In several regards, my research contributes to explaining why the latent trait of risk attitude rarely becomes evident in (experimental) choice behavior. I show that differences in option complexity, biases in visual attention (which to some extent overlap), individual differences in processing efficiency under selective attention, and biases in sampling behavior can profoundly shape preferences in risky choice tasks. This underlines and explains the constructed nature of these preferences, reminiscent of early work by Slovic (1995). My simulations in chapter 5 even suggest that choice behavior which appears indicative of risk seeking or risk aversion can emerge in the total absence of a latent disposition towards risk. Specifically, the aDDM, a model that does not assume a built-in disposition towards risk, can still implement (i.e. construct) apparently risk seeking and risk averse behavior.

This, admittedly, seems like an extreme idea. Yet, even if risky choice behavior is not *only* a consequence of construction processes, but to some extent also an expression of a stable disposition towards risk, the dispositional and the constructed components may often be misaligned. For instance, attentional biases towards safe or risky options emerge due to superficial features of options that have nothing to do with risk itself (e.g., their complexity, size, or salience, Orquin & Loose, 2013; Orquin et al., 2018). Hence, a person who has a latent disposition towards risk seeking, but who attends predominantly to safe options may produce choices that appear risk neutral or even risk averse. Moreover, intra-individually stable tendencies in attention allocation may systematically distort risk preferences measured in binary choice tasks—but be less consequential in other methods, such as self-reports. These insights may help explain the striking misalignment between different methods for measuring risk preference (Frey et al., 2017; Pedroni et al., 2017).

Moreover, having identified (some) concrete determinants of risky choice behavior, and the cognitive mechanisms by which they exert their influence, we are also in a position to make constructive suggestions for future research: When aiming to measure dispositional risk preference behaviorally, the disposition needs to be dissociated from the constructed component of behavior carefully, for instance via repeated or multi-method measurement. Differences in option complexity should be controlled for experimentally, and stimuli should be designed such that visual attention is not systematically drawn towards one visually distinctive option. For improving predictions of risky choice behavior in concrete situations, we (chapter 2) and others (Weber, 2010) have suggested that experimental choice tasks do not necessarily have to be de-confounded, but rather intentionally confounded to closely matches the features of the to-be predicted situation. For instance, classical choices between safe and risky options differing in option complexity may fare well at predicting behavior in an ecology where complexity and risk are confounded as well.

More generally, this work underlines that predicting risky choice behavior (in the lab or in the wild) can be a wildly different pursuit than measuring latent risk attitude. While psychometric measurement aims to isolate a stable trait, predicting concrete behavior requires to concurrently account for many contextual and psychological variables and their interplay.

6.2 Major Theoretical Contributions

The theoretical landscape on decision making under risk—with neo-Bernoullian and process models being arguably the most influential model families—can be framed in terms of Marr's computational and algorithmic levels of explanation (Marr, 1982). *Computational-level theories* identify the structure of the abstract problem that the mind solves, and define its ideal solution in functional terms, whereas *algorithminc-level theories* describe the concrete processes by which the mind approximates and executes the solution of this problem (cf. Griffiths et al., 2010; Griffiths et al., 2015). Neo-Bernoullian models like CPT identify a functional representation of the problems that humans seem to solve in risky choice. Process models such as aDDM or heuristics specify algorithms that approximate the solution of these abstract problems, while taking into account realistic constraints in processing and environments. These two types of models are often pitted against each other as competitors. My research illustrates 1) why this may not be a particularly meaning- or fruitful approach for evaluating models, and 2) how compatible insights from both frameworks can be identified and their relative strengths can be exploited instead, to make profound theoretical progress.

6.2.1 How can Models of Decision Making under Risk be Fairly Evaluated?

Marr's taxonomy is particularly helpful because it reminds us that neo-Bernoullian and process models of risky choice serve fundamentally different purposes. However, psychologists sometimes tend to assert—whether implicitly or explicitly—the primacy of the algorithmic level. For instance, neo-Bernoullian models of decision making under risk are sometimes interpreted as literal procedures, and judged according to their psychological realism. Maybe most prominently, the *as-if* critique questions if actual organisms might realistically compute CPT's functions (Berg & Gigerenzer, 2010). However, this argument either misunderstands or mischaracterizes computational-level theories. To abstract the structure of the problem that is solved by the mind, computational-level theories do not need to commit to specific cognitive processes (Griffiths et al., 2010)—this is, instead, the purpose of algorithmic-level theories. Consequently, psychological plausibility is only an appropriate standard for evaluating algorithmic-level theories.

These different purposes of computational- and algorithmic-level theories are easy to posit verbally. My analyses in chapter 5 substantiate them via simulations and recovery. I showed that choice patterns that result from a sequential sampling process—a psychologically plausible algorithm, which poses remarkably low demands on both arithmetic skills and memory, and which does not even require an explicit representation of probabilities—give rise to very characteristic shapes of CPT's probability-weighting function. Hence, an explicit mental representation and literal computation of CPT's functions is not necessary to produce behaviors that appear as if they had been computed in such a manner. This illustrates that CPT can much more meaningfully be understood as an abstract description of the *emergent properties* of simpler and psychologically more plausible processing strategies, than as a description of the process itself. This finding emphasizes the punchline of the as-if critique—CPT is not a process model—while at the same time exposing its false premise: Ironically, the as-if critique treats CPT *as if* it served to describe the choice process itself, and applies the (unfair) standard of psychological plausibility.

The failure to distinguish between computational-level and algorithmic-level models is, to some extent, intertwined with the common conflation between explanation and prediction (Shmueli, 2010). Marr (1982) subsumes both computational and algorithmic theories under the broad phrase "levels of *explanation*". By contrast, Shmueli (2010) more narrowly defines "*explanatory modeling* as the use of statistical models for testing causal explanations" (p. 290), thus distinguishing it from *predictive modeling*, as the application of models for predicting new observations, and *descriptive modeling*, as compactly summarizing the data structure (Shmueli, 2010). Hence, Marr's and Shmueli's taxonomies overlap in meaningful ways. While algorithmic-level theories rather *explain* the causal relations that gave rise to data on the process-level, computational-level theories compress systematic patterns which may allow to *predict* future observations—regardless of the underlying causality. Therefore, computational-level theories like CPT can be successful at describing and predicting behavior (cf. Glöckner & Pachur, 2012), without explaining the process in a plausible manner, and vice versa.

This further stresses that computational- and algorithmic-level theories address quite fundamentally different problems, which are interesting in their own right. Hence, asking the meta-theoretic question, which type of *problem* one wants to address (description, prediction, or explanation) can help clarify the standards for judging what constitutes a "good model", and constrain the range of theories which even qualify as serious competitors. Maybe most importantly, it also prevents one from wasting time on defeating theories that are not even playing the same ball game. However, this insight is very difficult to grasp under the partisan mindset of pitting different classes of theories against each other as competitors.

6.2.2 Can Computational-level Theories be Interpreted Psychologically?

Sober parameter estimates of formal models are typically not as compelling as psychological narratives. Hence, researchers have sometimes imposed psychological interpretations on neo-Bernoullian theories. For instance, although CPT's probability-weighting function makes no assumptions about psychological constructs like optimism or pessimism, they can, under specific parameter configurations, produce behaviors that conform to the intuitive idea of how an optimistic agent might act. As a consequence, such psychological interpretations become attached to the parameters themselves. My analyses in chapter 5 highlight why this can be problematic.

Inferring unobservable mental states from neuroimaging data posits a reverse inference problem (Poldrack, 2006, 2011). For instance, just because Broca's area is usually activated in language processing, one can not unequivocally infer from activity in this area that the person currently processes language—since different cognitive processes might activate this area as well. The same is true for inferring psychological characteristics from parameters of highly flexible models like CPT: To warrant such psychological inferences, it has to be shown convincingly that these parameters *selectively* respond to changes in the specific psychological process. In chapter 5, I show that both parameters of CPT's weighting function—the curvature and the elevation—covary very systematically with option-specific attentional biases. Hence interpretations in terms of optimism, pessimism or probability sensitivity (Abdellaoui et al., 2010; Gonzalez & Wu, 1999; Tversky & Kahneman, 1992) are not uncontested or unique. They may be misleading if not applied with great care, while excluding alternative explanations.

Neuroscientists have recognized reverse inference as a nontrivial problem and developed more sophisticated methods to infer unobservable mental states from neuroimaging data, such as multivariate pattern analysis (Haxby et al., 2014; Haynes & Rees, 2005). Moreover, databases like BrainMap make it easy to look up which psychological tasks are known to activate a given brain region and thus to approximate how confidently an inference can be made (cf. Poldrack, 2006). In modeling decision making under risk, basic awareness for the problem still seems to be lacking. The field would arguably benefit from systematically studying which psychological and non-psychological variables affect the parameter estimates in highly flexible computational-level models such as CPT, and compiling databases or meta-analyses of these findings. Much also remains to be learned from more classical psychometric methods, such as cross-validation, to asses how well parameters from computational models fare as measurement tools for psychological characteristics. To start approaching this challenge, a necessary first step is to identify diverse psychological interpretations for parameters in prominent theories like CPT. In chapter 5, I showcased how cross-theory parameter recovery between process models and computational-level theories can be used for this purpose.

6.2.3 What can Psychology Gain from Making Peace with Non-psychological Models?

Neo-Bernoullian models of decision making under risk are in essence non-psychological, and interpreting them psychologically can be problematic. So should psychologists exclusively focus on algorithmic-level theories, and stop caring about computational-level ones altogether? What is lost if the computational level is ignored? What can be gained by taking it seriously?

Anderson's (1991) *rational analysis* is one of the most prominent examples of psychologically useful computational-level explanation. Herein, human behavior is explained by assuming that it is optimized to affordances in the structure of the environment. This approach helps address pitfalls of explaining behavior based on specific mental processes alone. For instance, since many different mental mechanisms may cause equivalent behavioral consequences, there is a serious problem of identifiability. By positing that mental mechanism need to implement an optimal relationship between behaviors and environments, rational analysis constrains the vast range of conceivable mental mechanisms to a smaller number of plausible ones (Anderson, 1991).

More recently, Griffiths et al. (2010) have argued in favor of a top-down analysis of cognition starting with the (computational level) function of cognitive processes, and moving down towards the algorithms and implementations. They propose "beginning with abstract principles that allow agents to solve problems posed by the world—the functions that minds perform—and then attempting to reduce these principles to psychological and neural processes. Understanding the lower levels does not eliminate the need for higher-level models" (Griffiths et al., 2010, p. 357).

To substantiate this position, consider that computational-level models on decision making under risk constantly reference normative standards for rationality. Behavior is described in terms of deviations from such benchmarks, and the term "bias" pervades the literature. The aDDM literature emphasizes the process of forming preferences rather than comparing the resulting behavior to some normative standard. To recognize that the behavioral consequences of attentional processing dynamics in aDDM can systematically deviate from maximization, it helps to view the behavior of the process model through the lens of CPT (cf. chapter 5). And this exercise pays off: Establishing the link between processing dynamics and normative standards suggests concrete ways for improving maximization performance, by changing the process—for instance, by de-biasing attention. Since normative benchmarks are often not obvious, or specified at all, in algorithmic-level theories, such interventions are more difficult to design based on these theories alone. Hence, retaining the computational-level may be useful for psychologists to push the notion of rationality deeper towards the algorithmic level (Griffiths et al., 2015).

6.3 Conclusion

The human retina has no optic receptors in the area where the optic nerve attaches to the eyeball. Since the brain lacks sensory information about the corresponding contents of the visual field, humans have a natural blind spot in each eye. Yet, they are typically blissfully unaware of this blind spot, and astonished if their attention is drawn to it (Ramachandran, 1992a, 1992b). Conducing research on decision making under risk, while subscribing to a particular methodological or theoretical perspective, can cause a similar condition.

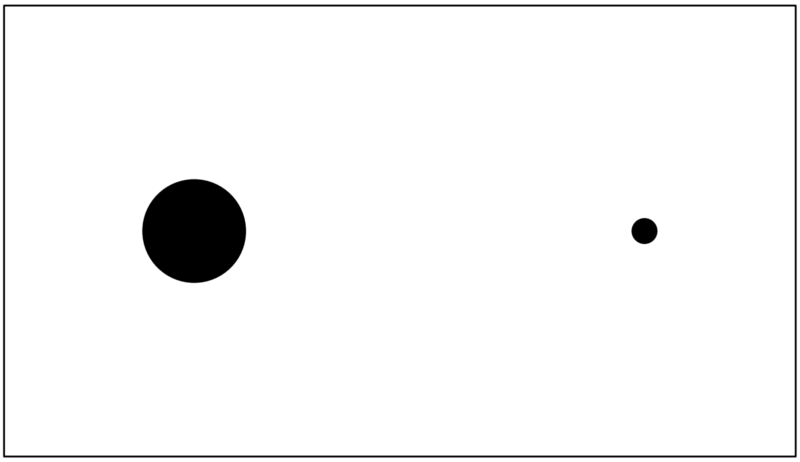

Figure 6.1: Demonstration of blind spots in the retina. If one closes the right eye, focuses the left eye's gaze on the right small circle and slowly moves the page towards oneself, at some point the larger left circle seems to disappear. Likewise, part of the world can disappear in plain sight when studying decision making under risk from an exclusive theoretical and methodological perspective.

For instance, the long-standing tradition of (neo-)Bernoullian models of risky choice has laid the groundwork for—and, to stay within the metaphor, opened our eyes to—starting to think about decision making under risk. Yet this tradition is blind to features of the world that come along with risks, and to psychological processes, which more often than not depart from normative calculus. Notably, these limits of the framework were not easily recognized by its proponents, even in the light of empirical findings which seemed inexplicable under the theoretical premises of EU. Instead, such evidence was often labelled "paradoxes" (cf. Allais, 1953; Birnbaum, 2008; Ellsberg, 1961)—a framing that rather questions the decision maker than the applied scientific approach. Another strategy to cope with such theoretical blind spots is to exploit the fact that models can fit data well either because they provide a good characterization of the truth, or simply because they are highly flexible (Lewandowsky & Farrell, 2018; Roberts & Pashler, 2000). Hence, resourceful modelers can usually find a solution to the conundrum posed by unexplained data, by making the model more flexible, while retaining its core assumptions. The neo-Bernoullian tradition excels at this strategy (cf. Berg & Gigerenzer, 2010). Yet, neither the first strategy—questioning the behavior itself—nor the second one—"fixing" the model by adding free parameters without revising its core assumptions—make a serious effort to understand where the methodological and theoretical approach falls short of being informative. So how can these elusive blind spots, which even come equipped with tools for explaining away their own existence, be overcome?

To experience perceptual failures caused by blind spots in the human retina, one typically needs to shut one eye (cf. Figure 6.1). This is because the human visual system can fill in the blind spot of the left eye by using sensory input from retinal cells of the right eye, and vice versa (Ramachandran, 1992a, 1992b). Likewise, complementary theoretical and methodological perspectives can help to fill in lacking information when studying decision making under risk. For instance, while neo-Bernoullian logic is well accomplished at abstractly describing behavior in relation to a normative standard, heuristics and sequential sampling models make it easy to think about psychological processes that may give rise to these patterns. Both issues can be difficult to even formulate in the other framework. As an almost direct consequence of such theoretical pluralism, scientists may also be motivated to consider higher-dimensional data. For instance, highly structured experiments relying on gambles have brought to light intriguing phenomena, such as the overweighting of certainty. Yet, in their traditional form, these tasks only elicit choice behavior, and thus make it easy to overlook the importance of information processing. Richer insights can be obtained by accompanying choices between gambles by process-tracing methods, such as eye-tracking, or by explicitly building the search process into the choice task itself, as in the sampling paradigm. To dive even deeper into the implementation of such processes, turning towards neuroscientific data may be a logical next step.

In essence, each conceptual and experimental framework makes it easy to think about certain aspects of risky choice, but not others, and thereby determines which kinds of inferences we (can) make. So far, no individual framework covers all of these aspects comprehensively. Until such an overarching framework is found, a multi-method and multi-theory approach—such as the one applied in this dissertation—can serve as a vision-aid for the blind spots that currently exist in individual branches of research on decision making under risk.

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Appendices

A | Supplemental Materials to Chapter 2

A.1 Manipulation Checks

Participants' choices of the dominant option in both studies were analyzed with Bayesian GLMERs, including problem type, age group, their interaction, EV difference, and numeracy scores as fixed effects, and a random intercept for each participant. The results are displayed in the top panel of Table A.1 (Study 1) and Table A.2 (Study 2) and illustrated in Figure A.1. The negative main effect of the complex safe condition indicates that participants were more likely to choose the dominant option in the problems with simple safe options (in both domains in Study 2 and in the loss domain in Study 1). In both studies and across both domains, participants with higher numeracy scores were more likely to choose the dominant option. In Study 1, younger and older adults did not differ in their choice of the dominant option, and in Study 2 older adults were less likely to choose the dominant option, in both domains. There were no interactions between problem type and age group in either study.

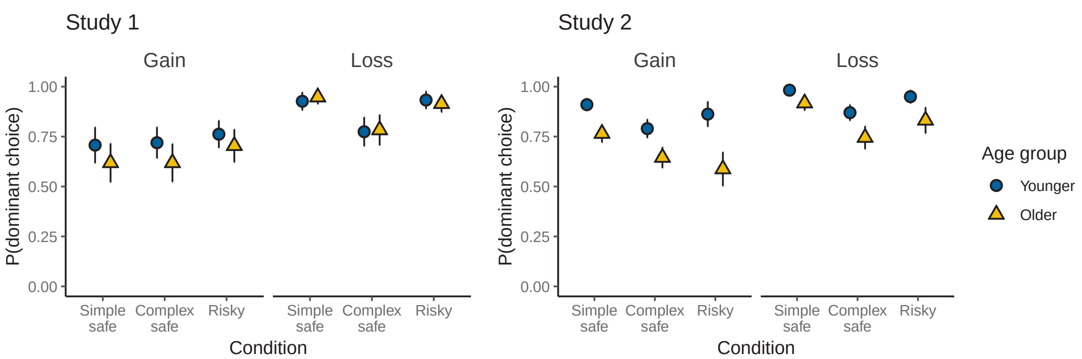

Figure A.1: Choice proportions for the dominated problems in all conditions and age groups by domain in Study 1. Error bars indicate 95% confidence intervals.

We also used Bayesian GLMERs to analyze participants' complexity ratings of the different types of choice problems including problem type, age group, their interaction, EV difference, self-reported risk preferences and numeracy scores as fixed effects, and a random intercept for each participant. Results from the analysis of complexity ratings are displayed in the middle panel of Table A.1 (Study 1) and Table A.2 (Study 2) and illustrated in Figure A.2. In both studies and domains, participants rated problems from the complex safe condition and from the risky condition as more complex than problems from the simple safe condition. In Study 2, participants rated problems with a zero outcome in the domain of gains as less complex compared to the corresponding problem type that did not involve zero outcomes. In addition, problems with higher EV differences between the options were rated as less complex, and problems in which the higher EV option was more risky were perceived as more complex. In Study 1, there was no credible main effect of age group on the complexity ratings, indicating that viewed across all conditions, older and younger adults did not differ in their perception of complexity. In Study 2, the credible positive main effect of age group in the domain of gains indicates that older adults overall rated problems as more complex. There was a credible negative interaction between problem type (complex safe) and age group in the domain of gains (Study 2) and in the domain of losses (Study 1), indicating that older adults' complexity ratings increased less than younger adults' in the condition with complex safe compared to simple safe options.

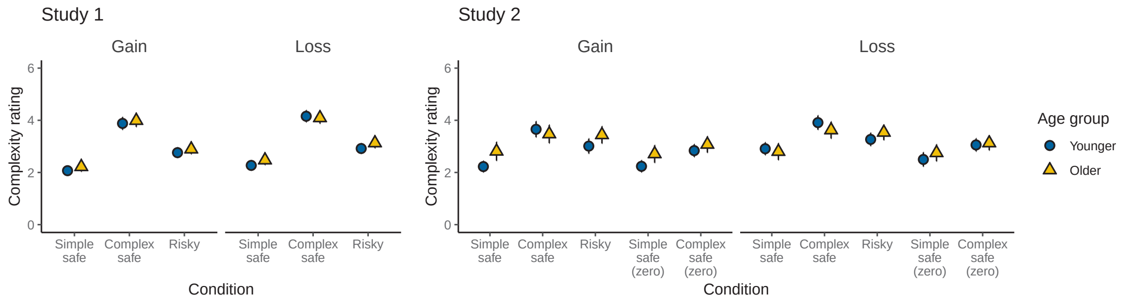

Figure A.2: Complexity ratings for nondominated problems in all conditions and age groups by domain in Study 1. Error bars indicate 95% confidence intervals.

Finally, we used Bayesian GLMERs to analyze participants' RTs on the non-dominated choice problems. These models included problem type, age group, their interaction, a binary variable indicating whether the option with the higher EV was also more risky, EV difference, numeracy scores, and self-reported risk preference as fixed effects, and a random intercept for each participant. Results are displayed in the bottom panel of Table A.1 (Study 1) and Table A.2 (Study 2) and illustrated in Figure A.3. Participants took more time to respond in the complex safe condition and in the risky condition, compared to the simple safe condition. Older adults overall took longer to make choices than younger adults. In Study 1, participants with higher numeracy scores also generally took longer to make choices in the domain of gains. On trials with larger EV differences (which are easier) RTs were shorter in the domain of gains (both studies) and the domain of losses (Study 2). Finally, an interaction between problem type (complex safe) and age group (older) indicates that older adults' RTs increased more substantially when the complexity of safe options increased than younger adults'. In Study 2, participants took less time on choice problems with risky options offering a zero outcome, compared to the corresponding problems where no zero outcome was available.

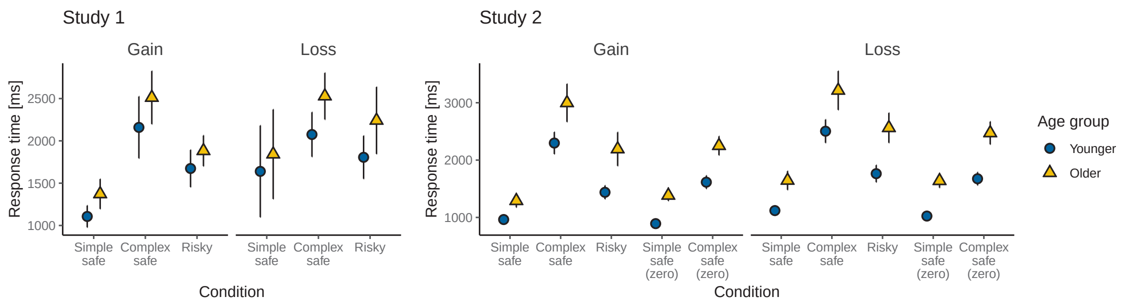

Figure A.3: Response times for nondominated problems in all conditions and age groups by domain in Study 1. Error bars indicate 95% confidence intervals.

Table A.1: Regression Coefficients and 95% Posterior Intervals From the Mixed-Effects Regression of Participants' Responses on the Dominated Choice Problems, Participants' Responses on the Complexity Rating Task, and Response Times on the Problems without a Dominated Option, Separately for Problems in the Gain and Loss Domain, in Study 1

Outcome Variable (Study 1)	Main effect model		Interaction model	
Predictor	Gain	Loss	Gain	Loss
Choices on dominated problems				
(Intercept)	**-2.44** **[-3.59, -1.25]**	**2.18** **[0.95, 3.53]**	**-2.45** **[-3.66, -1.31]**	**2.03** **[0.7, 3.37]**
Problem Type (Complex Safe)	0.04 [-0.39, 0.47]	**-1.75** **[-2.35, -1.2]**	0.09 [-0.49, 0.71]	**-1.64** **[-2.4, -0.92]**
Problem Type (Risky)	**0.54** **[0.11, 1]**	-0.21 [-0.85, 0.44]	0.45 [-0.17, 1.06]	0.09 [-0.74, 1]
Age Group (Older)	-0.28 [-0.96, 0.37]	0.13 [-0.51, 0.75]	-0.31 [-1.14, 0.53]	0.46 [-0.59, 1.51]
EV Difference	**0.28** **[0.1, 0.46]**	0.03 [-0.2, 0.24]	**0.28** **[0.1, 0.46]**	0.03 [-0.2, 0.25]
Numeracy	**1.07** **[0.79, 1.39]**	**0.46** **[0.17, 0.75]**	**1.08** **[0.78, 1.4]**	**0.47** **[0.19, 0.78]**
Problem Type (Complex Safe) × Age Group (Older)			-0.09 [-0.91, 0.73]	-0.26 [-1.39, 0.82]
Problem Type (Risky) × Age Group (Older)			0.2 [-0.66, 1.1]	-0.65 [-1.99, 0.59]
Complexity rating				
(Intercept)	**2.27** **[1.82, 2.73]**	**2.44** **[2.02, 2.87]**	**2.23** **[1.79, 2.66]**	**2.42** **[1.98, 2.83]**
Problem Type (Complex Safe)	**1.79** **[1.69, 1.88]**	**1.74** **[1.65, 1.84]**	**1.81** **[1.68, 1.95]**	**1.86** **[1.73, 1.99]**
Problem Type (Risky)	**0.69** **[0.6, 0.78]**	**0.66** **[0.56, 0.75]**	**0.7** **[0.57, 0.83]**	**0.65** **[0.52, 0.78]**
Age Group (Older)	0.13 [-0.1, 0.37]	0.1 [-0.1, 0.32]	0.16 [-0.11, 0.4]	0.18 [-0.07, 0.43]
Higher EV Choice = Higher CV Choice	**0.09** **[0.02, 0.17]**	**0.15** **[0.07, 0.23]**	**0.09** **[0.01, 0.17]**	**0.15** **[0.07, 0.23]**
EV Difference	**-0.01** **[-0.02, -0.01]**	**-0.01** **[-0.01, -0.01]**	**-0.01** **[-0.02, -0.01]**	**-0.01** **[-0.01, -0.01]**
Numeracy	0.01 [-0.08, 0.11]	-0.03 [-0.13, 0.05]	0.02 [-0.07, 0.11]	-0.04 [-0.13, 0.05]
Self-reported Risk Preference	0 [-0.06, 0.05]	0.01 [-0.03, 0.06]	0 [-0.05, 0.05]	0.01 [-0.03, 0.06]
Problem Type (Complex Safe) × Age Group (Older)			-0.05 [-0.25, 0.13]	**-0.25** **[-0.44, -0.05]**
Problem Type (Risky) × Age Group (Older)			-0.02 [-0.21, 0.17]	0.01 [-0.18, 0.21]
Response times				
(Intercept)	**785.74** **[225.59, 1337.38]**	**1277.03** **[483.53, 2091.94]**	**786.83** **[260.85, 1335.25]**	**1351.92** **[546.74, 2156.8]**
Problem Type (Complex Safe)	**1093.15** **[927.97, 1261.5]**	**555.8** **[220.05, 887.8]**	**1054.28** **[832.86, 1282.67]**	436.21 [-22.29, 900.14]
Problem Type (Risky)	**538.8** **[375.51, 706.72]**	274.21 [-51.18, 608.65]	**569.09** **[342.51, 797.01]**	162.13 [-293.3, 643.44]
Age Group (Older)	**340.64** **[61.26, 601.76]**	**411.87** **[53.58, 778.87]**	325.17 [-5.96, 653.89]	257.5 [-279.37, 803.24]
Higher EV Choice = Higher CV Choice	-5.36 [-137.66, 128.9]	-221.86 [-495.13, 59.19]	-4.27 [-133.67, 125.32]	-220.78 [-499.12, 53.19]
EV Difference	**-13.03** **[-19.25, -6.55]**	-7.31 [-20.56, 5.55]	**-12.93** **[-19.27, -6.61]**	-7.15 [-20.74, 5.68]
Numeracy	**123.38** **[5.86, 237.61]**	91.47 [-65.31, 251.93]	**121.42** **[12.24, 239.3]**	93.52 [-63.56, 246.04]
Self-reported Risk Preference	46.39 [-14.8, 108.32]	52.7 [-26.57, 134.2]	46.54 [-14.77, 108.01]	53.29 [-31.04, 135.12]
Problem Type (Complex Safe) × Age Group (Older)			84.25 [-242.27, 425.24]	252.31 [-430.76, 898.86]
Problem Type (Risky) × Age Group (Older)			-61.61 [-391.07, 276.95]	235.51 [-417.99, 874.47]

Table A.2: Regression Coefficients and 95% Posterior Intervals From the Mixed-Effects Regression of Participants' Responses on the Dominated Choice Problems, Participants' Responses on the Complexity Rating Task, and Response Times on the Nondominated Problems, Separately for Problems in the Gain and Loss Domain, in Study 2

Outcome Variable (Study 2)	Main effect model		Interaction model	
Predictor	Gain	Loss	Gain	Loss
Choices on dominated problems				
(Intercept)	**2.32 [1.77, 2.88]**	**3.27 [2.42, 4.17]**	**2.42 [1.83, 3.05]**	**3.61 [2.58, 4.63]**
Problem Type (Complex Safe)	**-0.83 [-1.08, -0.57]**	**-1.76 [-2.17, -1.39]**	**-1.09 [-1.54, -0.66]**	**-2.2 [-2.99, -1.46]**
Problem Type (Risky)	**-0.7 [-1.04, -0.37]**	**-1.01 [-1.55, -0.45]**	-0.43 [-1.02, 0.19]	**-1.05 [-2.03, -0.01]**
Age Group (Older)	**-0.95 [-1.31, -0.61]**	**-0.94 [-1.48, -0.44]**	**-1.08 [-1.61, -0.58]**	**-1.36 [-2.23, -0.49]**
EV Difference	**-0.14 [-0.24, -0.04]**	0.05 [-0.11, 0.23]	**-0.14 [-0.24, -0.04]**	0.06 [-0.12, 0.23]
Numeracy	**0.26 [0.11, 0.42]**	**0.33 [0.1, 0.57]**	**0.26 [0.1, 0.43]**	**0.34 [0.11, 0.58]**
Problem Type (Complex Safe) × Age Group (Older)			0.41 [-0.11, 0.97]	0.6 [-0.27, 1.5]
Problem Type (Risky) × Age Group (Older)			-0.43 [-1.18, 0.26]	0.03 [-1.14, 1.16]
Complexity rating				
(Intercept)	**2.76 [2.29, 3.24]**	**3.47 [3.04, 3.91]**	**2.67 [2.16, 3.17]**	**3.56 [3.1, 4.01]**
Problem Type (Simple Safe Zero)	**-0.24 [-0.46, -0.01]**	**-0.52 [-0.75, -0.29]**	-0.23 [-0.51, 0.08]	**-0.73 [-1.03, -0.43]**
Problem Type (Complex Safe)	**1.07 [0.89, 1.26]**	**0.93 [0.74, 1.11]**	**1.39 [1.14, 1.66]**	**1.02 [0.77, 1.28]**
Problem Type (Complex Safe Zero)	0.15 [-0.08, 0.37]	-0.12 [-0.33, 0.12]	0.27 [-0.01, 0.58]	-0.18 [-0.46, 0.11]
Problem Type (Risky)	**0.76 [0.58, 0.94]**	**0.66 [0.47, 0.85]**	**0.78 [0.52, 1.04]**	**0.44 [0.18, 0.71]**
Age Group (Older)	**0.36 [0.1, 0.64]**	0.06 [-0.19, 0.33]	**0.55 [0.19, 0.91]**	-0.09 [-0.43, 0.26]
Higher EV Choice = Higher CV Choice	**0.16 [0.04, 0.27]**	-0.1 [-0.22, 0.02]	**0.15 [0.03, 0.27]**	-0.1 [-0.21, 0.01]
EV Difference	**-0.02 [-0.02, -0.01]**	**-0.02 [-0.02, -0.01]**	**-0.02 [-0.02, -0.01]**	**-0.02 [-0.02, -0.01]**
Numeracy	0.03 [-0.1, 0.15]	0.02 [-0.09, 0.14]	0.03 [-0.1, 0.15]	0.02 [-0.08, 0.13]
Self-reported Risk Preference	-0.06 [-0.12, 0]	**-0.07 [-0.13, -0.01]**	-0.06 [-0.12, 0]	**-0.07 [-0.13, -0.02]**
Problem Type (Simple Safe Zero) × Age Group (Older)			-0.02 [-0.41, 0.35]	**0.4 [0.02, 0.77]**
Problem Type (Complex Safe) × Age Group (Older)			**-0.65 [-1.03, -0.28]**	-0.16 [-0.54, 0.19]
Problem Type (Complex Safe Zero) × Age Group (Older)			-0.25 [-0.62, 0.12]	0.12 [-0.22, 0.49]
Problem Type (Risky) × Age Group (Older)			-0.06 [-0.44, 0.31]	**0.42 [0.06, 0.78]**
Response times				
(Intercept)	**1074.06 [750.88, 1396.62]**	**1195.55 [813.02, 1560.83]**	**1184.61 [881.42, 1518.27]**	**1291.54 [908.33, 1669.54]**
Problem Type (Simple Safe Zero)	**-253.62 [-342.08, -171.64]**	**-302.7 [-399.3, -208.82]**	**-334.65 [-445.1, -222.36]**	**-349.31 [-472.15, -224.44]**
Problem Type (Complex Safe)	**1519.59 [1448.89, 1588.87]**	**1476.37 [1400.92, 1551.19]**	**1332.06 [1233.68, 1430.31]**	**1382.79 [1271.32, 1487.44]**
Problem Type (Complex Safe Zero)	**540.56 [452.49, 627.24]**	**437.56 [340.52, 533.45]**	**387.12 [274.84, 497.91]**	**301.58 [182.15, 421.55]**
Problem Type (Risky)	**687.64 [619.85, 757.32]**	**779.19 [703.84, 854.68]**	**474.54 [372.72, 576.26]**	**640.93 [536.01, 747.2]**
Age Group (Older)	**615.15 [406.36, 829.46]**	**724.44 [520.23, 952.58]**	**352.85 [125.01, 573.59]**	**555.69 [308.33, 813.09]**
Higher EV Choice = Higher CV Choice	21.83 [-21.56, 65.75]	17.46 [-29.74, 65.31]	22.09 [-21.83, 65.05]	17.03 [-28.99, 63.54]
EV Difference	**-13.44 [-16.1, -10.73]**	**-12.99 [-15.96, -10.08]**	**-13.42 [-16.12, -10.88]**	**-12.92 [-15.83, -10.02]**
Numeracy	46.55 [-42.34, 131.83]	70.13 [-32.07, 170.7]	46.26 [-44.64, 133.8]	74.35 [-25.94, 175.72]
Self-reported Risk Preference	-12.05 [-56.9, 32.17]	-9.48 [-61.19, 46.2]	-10.84 [-54.13, 31.21]	-13.01 [-59.74, 36.26]
Problem Type (Simple Safe Zero) × Age Group (Older)			**164.55 [23.8, 306.67]**	94.08 [-52, 241.34]
Problem Type (Complex Safe) × Age Group (Older)			**375.34 [229.5, 512.48]**	**189.75 [44.57, 344.53]**
Problem Type (Complex Safe Zero) × Age Group (Older)			**308.72 [171.72, 451.05]**	**275.09 [129.01, 427.46]**
Problem Type (Risky) × Age Group (Older)			**427.83 [282.77, 575.83]**	**276.83 [133.1, 430.14]**

A.2 Analysis of Risky Choice Patterns within Individual Conditions and Age Groups

Table A.3: Regression Coefficients and 95% Posterior Intervals From the Mixed-Effects Logistic Regression of Responses in the Risky Choice Task of Study 1, by Condition. Outcome Variable: Choice of the More Risky Option

Outcome Variable: Choice of Option with Higher Risk (Study 1)	Gain			Loss		
Predictor	Simple Safe	Complex Safe	Risky	Simple Safe	Complex Safe	Risky
(Intercept)	**-3.12** **[-3.74, -2.51]**	**-1.89** **[-2.46, -1.36]**	**-2.6** **[-3.07, -2.15]**	**-0.48** **[-0.9, -0.04]**	0.13 [-0.38, 0.65]	-0.34 [-0.71, 0.03]
Age Group (Older)	**-0.48** **[-0.76, -0.18]**	0.02 [-0.26, 0.29]	-0.14 [-0.33, 0.06]	**0.32** **[0.12, 0.52]**	0.11 [-0.14, 0.37]	0.04 [-0.13, 0.22]
Higher EV Choice = Higher CV Choice	**2.49** **[2.28, 2.7]**	**1.99** **[1.8, 2.18]**	**2.53** **[2.34, 2.73]**	**1.36** **[1.19, 1.53]**	**1.13** **[0.96, 1.3]**	**1.22** **[1.06, 1.39]**
EV Difference	**0.02** **[0.01, 0.03]**	0.01 [0, 0.01]	**0.03** **[0.02, 0.04]**	0.01 [0, 0.01]	-0.01 [-0.02, 0]	-0.01 [-0.02, 0]
Numeracy	**0.28** **[0.16, 0.41]**	**0.15** **[0.03, 0.27]**	0.05 [-0.04, 0.13]	-0.05 [-0.14, 0.04]	-0.06 [-0.17, 0.05]	0.01 [-0.07, 0.08]
Self-reported Risk Preference	0.03 [-0.04, 0.09]	0.01 [-0.05, 0.07]	0.02 [-0.03, 0.06]	-0.02 [-0.06, 0.03]	-0.01 [-0.07, 0.04]	0.01 [-0.03, 0.05]
Gender (Male)	0.19 [-0.11, 0.5]	0.2 [-0.08, 0.47]	0.17 [-0.03, 0.37]	-0.1 [-0.3, 0.11]	-0.24 [-0.5, 0]	0.04 [-0.13, 0.22]

Table A.4: Regression Coefficients and 95% Posterior Intervals From the Mixed-Effects Logistic Regression of Responses in the Risky Choice Task of Study 2, by Condition. Outcome Variable: Choice of the More Risky Option

Outcome Variable: Choice of Option with Higher Risk (Study 2)	Gain					Loss				
Predictor	Simple Safe	Complex Safe	Risky	Simple Safe (Zero)	Complex Safe (Zero)	Simple Safe	Complex Safe	Risky	Simple Safe (Zero)	Complex Safe (Zero)
(Intercept)	**-4.48** **[-5.32, -3.66]**	**-2.77** **[-3.41, -2.16]**	**-2.8** **[-3.25, -2.36]**	**-1.58** **[-2.25, -0.9]**	**-1.31** **[-1.95, -0.66]**	**-0.99** **[-1.56, -0.46]**	**-0.81** **[-1.34, -0.31]**	**-0.91** **[-1.45, -0.39]**	**-1.26** **[-1.83, -0.73]**	**-0.91** **[-1.45, -0.38]**
Age Group (Older)	**-0.72** **[-1.21, -0.23]**	-0.08 [-0.44, 0.26]	**-0.3** **[-0.51, -0.08]**	-0.29 [-0.69, 0.11]	-0.03 [-0.43, 0.38]	-0.06 [-0.41, 0.28]	-0.07 [-0.38, 0.25]	0.16 [-0.12, 0.43]	0.15 [-0.21, 0.49]	-0.08 [-0.43, 0.25]
Higher EV Choice = Higher CV Choice	**3.82** **[3.52, 4.12]**	**2.45** **[2.23, 2.66]**	**2.89** **[2.67, 3.12]**	**1.54** **[1.34, 1.75]**	**1.46** **[1.26, 1.65]**	**2.28** **[2.09, 2.47]**	**1.85** **[1.68, 2.02]**	**3.04** **[2.76, 3.32]**	**2.15** **[1.93, 2.37]**	**1.87** **[1.67, 2.09]**
EV Difference	0.01 [0, 0.03]	**0.02** **[0.01, 0.03]**	**0.02** **[0.01, 0.03]**	**-0.63** **[-0.72, -0.54]**	**-0.4** **[-0.48, -0.31]**	0.01 [0, 0.02]	0 [-0.01, 0.01]	-0.02 [-0.03, 0]	0.01 [0, 0.02]	0 [-0.01, 0.01]
Numeracy	**0.23** **[0.03, 0.45]**	0.08 [-0.08, 0.23]	0.04 [-0.06, 0.13]	0.15 [-0.03, 0.32]	0.1 [-0.06, 0.28]	-0.08 [-0.23, 0.07]	-0.06 [-0.2, 0.08]	0.01 [-0.11, 0.13]	-0.01 [-0.16, 0.13]	-0.03 [-0.18, 0.12]
Self-reported Risk Preference	**0.13** **[0.03, 0.24]**	**0.1** **[0.03, 0.18]**	0.03 [-0.02, 0.08]	**0.14** **[0.05, 0.23]**	**0.15** **[0.06, 0.24]**	0.01 [-0.06, 0.09]	0.02 [-0.05, 0.09]	-0.01 [-0.07, 0.05]	0.04 [-0.03, 0.12]	0.02 [-0.05, 0.1]
Gender (Male)	0.05 [-0.4, 0.51]	0.01 [-0.34, 0.33]	0.16 [-0.06, 0.38]	0.27 [-0.11, 0.65]	0.11 [-0.29, 0.5]	0.19 [-0.14, 0.51]	0.15 [-0.16, 0.45]	-0.18 [-0.46, 0.08]	0.2 [-0.13, 0.52]	0.14 [-0.19, 0.48]

We conducted Bayesian mixed-effects logistic regressions to predict the choice of the more risky option, within each individual condition, using age group as a fixed effect. The models further included fixed effects for the EV difference between the options, a dummy variable indicating whether the option with the higher EV was also more risky, each participant's numeracy score, and their self-reported risk preference and gender. The model included a random intercept for each participant. Results for condition-wise analyses are displayed in Table A.3 for Study 1 and Table A.4 for Study 2. In choices between simple safe and risky options, older adults were credibly less risk seeking than younger adults in the domain of gains (both studies) and credibly more risk seeking than younger adults in the domain of losses (Study 1). In the condition with complex safe options and the condition with two risky options, there were no credible age differences in either study. This speaks to our hypothesis that age differences in risk preference are reduced or eliminated when options are similarly complex.

We also conducted Bayesian mixed-effects logistic regressions to predict the choice of the more risky option, within each individual age group, using condition as a fixed effect. The models further included fixed effects for the EV difference between the options, a dummy variable indicating whether the option with the higher EV was also more risky, each participant's numeracy score, and their self-reported risk preference and gender. The model included a random intercept for each participant. Results for the analyses by age group are displayed in Table A.5. In both studies, older adults were more likely to choose the more risky option in choices between complex safe and risky options and in choices between two risky options, compared to choices with simple safe options, in the domain of gains. In the domain of losses, older adults were less likely to choose the more risky

Table A.5: Regression Coefficients and 95% Posterior Intervals From the Mixed-Effects Logistic Regression of Responses in the Risky Choice Task of Study 1 (Upper Table) and Study 2 (Lower Table), by Age Group. Outcome Variable: Choice of the More Risky Option

Outcome Variable: Choice of Option with Higher Risk (Study 1)	Gain		Loss	
Predictor	Young	Old	Young	Old
(Intercept)	**-2.35** **[-2.85, -1.84]**	**-3.28** **[-3.87, -2.7]**	**-0.46** **[-0.85, -0.08]**	0.3 [-0.14, 0.73]
Problem Type (Complex Safe)	**0.19** **[0.01, 0.38]**	**0.69** **[0.49, 0.88]**	0.03 [-0.14, 0.2]	-0.16 [-0.33, 0.01]
Problem Type (Risky)	0.06 [-0.13, 0.23]	**0.44** **[0.24, 0.63]**	0.06 [-0.1, 0.23]	**-0.24** **[-0.4, -0.08]**
Higher EV Choice = Higher CV Choice	**2.33** **[2.17, 2.48]**	**2.26** **[2.09, 2.42]**	**1.33** **[1.19, 1.47]**	**1.12** **[0.98, 1.26]**
EV Difference	**0.01** **[0.01, 0.02]**	**0.02** **[0.01, 0.03]**	0 [-0.01, 0]	-0.01 [-0.01, 0]
Numeracy	**0.16** **[0.07, 0.27]**	0.14 [0, 0.27]	0.04 [-0.04, 0.12]	**-0.1** **[-0.21, -0.01]**
Self-reported Risk Preference	-0.01 [-0.07, 0.04]	0.06 [-0.01, 0.13]	-0.01 [-0.05, 0.03]	-0.01 [-0.07, 0.05]
Gender (Male)	0.2 [-0.05, 0.42]	0.1 [-0.21, 0.42]	**-0.2** **[-0.38, -0.01]**	-0.02 [-0.25, 0.23]

Outcome Variable: Choice of Option with Higher Risk (Study 2)	Gain		Loss	
Predictor	Young	Old	Young	Old
(Intercept)	**-3.03** **[-3.52, -2.52]**	**-3.05** **[-3.67, -2.47]**	-0.41 [-0.93, 0.09]	**-0.81** **[-1.32, -0.28]**
Problem Type (Simple Safe Zero)	0.16 [-0.08, 0.4]	**0.42** **[0.19, 0.66]**	**-0.42** **[-0.65, -0.18]**	**-0.44** **[-0.65, -0.23]**
Problem Type (Complex Safe)	**0.31** **[0.13, 0.5]**	**0.75** **[0.56, 0.94]**	-0.07 [-0.27, 0.13]	**-0.38** **[-0.56, -0.2]**
Problem Type (Complex Safe Zero)	**0.65** **[0.41, 0.88]**	**1.1** **[0.88, 1.34]**	**-0.42** **[-0.65, -0.18]**	**-0.38** **[-0.59, -0.16]**
Problem Type (Risky)	**0.23** **[0.05, 0.43]**	**0.53** **[0.34, 0.72]**	-0.16 [-0.35, 0.04]	**-0.21** **[-0.39, -0.03]**
Higher EV Choice = Higher CV Choice	**2.4** **[2.28, 2.53]**	**1.77** **[1.65, 1.89]**	**2.46** **[2.33, 2.58]**	**1.97** **[1.85, 2.08]**
EV Difference	**0.01** **[0.01, 0.02]**	0.01 [0, 0.02]	-0.01 [-0.01, 0]	-0.01 [-0.01, 0]
Numeracy	0.04 [-0.07, 0.17]	**0.21** **[0.02, 0.42]**	**-0.14** **[-0.27, -0.01]**	0.11 [-0.07, 0.29]
Self-reported Risk Preference	**0.11** **[0.05, 0.18]**	0.08 [-0.02, 0.17]	0.01 [-0.06, 0.08]	0.01 [-0.07, 0.09]
Gender (Male)	0.29 [0, 0.59]	-0.09 [-0.48, 0.33]	-0.05 [-0.38, 0.28]	0.27 [-0.08, 0.61]

option in choices between complex safe and risky options (Study 2) and in choices between two risky options (both studies), compared to the condition with simple safe options. Younger adults' behavior tended to change in the same directions, but the effects were weaker or not credible. This further supports the hypothesis that older adults are more sensitive to complexity differences than younger adults.

A.3 Analysis of Risky Choice In Choice Problems Offering A Risky Outcome of Zero

Table A.6: Regression Coefficients and 95% Posterior Intervals from the Bayesian Mixed-Effects Logistic Regression for Responses in the Risky Choice Task in Study 2. Reference Condition: Simple Safe Zero

Outcome Variable: Choice of Option with Higher Risk (Study 2, reference simple safe zero)	Main effect model		Interaction model	
Predictor	Gain	Loss	Gain	Loss
(Intercept)	**-2.65** **[-3.07, -2.23]**	**-1.04** **[-1.44, -0.64]**	**-2.64** **[-3.06, -2.2]**	**-1.05** **[-1.47, -0.66]**
Problem Type (Simple Safe)	**-0.29** **[-0.45, -0.13]**	**0.43** **[0.26, 0.59]**	-0.16 [-0.36, 0.05]	**0.4** **[0.2, 0.6]**
Problem Type (Complex Safe)	**0.25** **[0.08, 0.4]**	**0.19** **[0.03, 0.35]**	0.14 [-0.07, 0.34]	**0.33** **[0.13, 0.53]**
Problem Type (Complex Safe Zero)	**0.58** **[0.46, 0.71]**	0.03 [-0.1, 0.16]	**0.47** **[0.28, 0.64]**	0 [-0.18, 0.18]
Problem Type (Risky)	0.09 [-0.07, 0.24]	**0.24** **[0.08, 0.4]**	0.06 [-0.15, 0.27]	**0.25** **[0.04, 0.44]**
Age Group (Older)	-0.23 [-0.48, 0.03]	-0.01 [-0.26, 0.24]	-0.28 [-0.59, 0.03]	0.03 [-0.26, 0.34]
Higher EV Choice = Higher CV Choice	**2.09** **[2, 2.17]**	**2.2** **[2.12, 2.28]**	**2.09** **[2, 2.18]**	**2.21** **[2.12, 2.3]**
EV Difference	**0.01** **[0.01, 0.02]**	-0.01 [-0.01, 0]	**0.01** **[0.01, 0.02]**	-0.01 [-0.01, 0]
Numeracy	0.11 [-0.01, 0.22]	-0.04 [-0.15, 0.06]	0.11 [0, 0.22]	-0.04 [-0.15, 0.07]
Self-reported Risk Preference	**0.1** **[0.04, 0.15]**	0.01 [-0.04, 0.07]	**0.1** **[0.04, 0.16]**	0.01 [-0.04, 0.06]
Gender (Male)	0.11 [-0.13, 0.35]	0.13 [-0.12, 0.36]	0.1 [-0.17, 0.36]	0.13 [-0.1, 0.37]
Problem Type (Simple Safe) × Age Group (Older)			**-0.28** **[-0.55, -0.02]**	0.06 [-0.2, 0.31]
Problem Type (Complex Safe) × Age Group (Older)			0.22 [-0.05, 0.47]	**-0.28** **[-0.53, -0.03]**
Problem Type (Complex Safe Zero) × Age Group (Older)			0.24 [-0.01, 0.5]	0.07 [-0.19, 0.31]
Problem Type (Risky) × Age Group (Older)			0.06 [-0.21, 0.32]	-0.02 [-0.26, 0.24]

In Study 2, we included two new conditions to test for a positive (negative) interaction between age and option complexity on the tendency to choose the option with the higher risk when a risky outcome of zero was available in the domain of gains (losses). To test for these effects, we conducted Bayesian mixed-effects logistic regressions to predict the choice of the more risky option in Study 2, using problem type and age group (main effect model) as well as their interaction (interaction model) as fixed effects. For these models we changed the reference level for the factor problem type to the simple safe zero condition. The models further included fixed effects for the EV difference between options, a dummy variable indicating whether the option with the higher EV was also more risky, each participant's numeracy score, gender, and their self-reported risk preference. Coefficients and 95% posterior intervals are displayed in Table A.6. There was no credible interaction between problem type complex safe zero and age group in either domain. Note that there were already no age differences in choices between simple safe options and risky options with zero outcomes (which are more similar in their complexity, compared to choices with simple safe options and risky options without zero outcomes; cf. Appendix A.2). Hence, rendering the options even more similar in their complexity, by increasing the complexity of safe options, could not further reduce the (already absent) age differences in risky choice behavior.

A.4 Testing the Effect of Certainty on the CPT Parameters

Table A.7: Regression Coefficients From the Regressions on CPT Parameters in Study 1. Reference Condition: Complex Safe. Reference Age Group: Older Adults

Outcome Variable (Study 1) / Predictor	Gain: Main effect model	Gain: Interaction model	Loss: Main effect model	Loss: Interaction model
ρ (response noise)				
(Intercept)	**0.1 [0.09, 0.11]**	**0.09 [0.07, 0.1]**	**0.18 [0.16, 0.2]**	**0.16 [0.14, 0.19]**
Age Group (Older)	**-0.03 [-0.04, -0.02]**	-0.01 [-0.02, 0.01]	**-0.07 [-0.09, -0.05]**	-0.03 [-0.07, 0]
Problem Type (Risky)	**0.07 [0.06, 0.08]**	**0.09 [0.07, 0.11]**	0.01 [-0.01, 0.04]	0.03 [0, 0.07]
Problem Type (Risky) × Age Group (Older)		**-0.04 [-0.07, -0.02]**		-0.04 [-0.09, 0.01]
Problem Type (Simple Safe)	**0.1 [0.09, 0.11]**	**0.12 [0.1, 0.13]**	**0.09 [0.07, 0.12]**	**0.12 [0.09, 0.16]**
Problem Type (Simple Safe) × Age Group (Older)		**-0.04 [-0.06, -0.01]**		**-0.06 [-0.11, -0.01]**
γ (probability weighting)				
(Intercept)	**1.21 [1.16, 1.26]**	**1.22 [1.16, 1.28]**	**1.17 [1.13, 1.21]**	**1.07 [1.03, 1.12]**
Age Group (Older)	-0.06 [-0.11, 0]	-0.08 [-0.17, 0.01]	-0.02 [-0.07, 0.02]	**0.17 [0.1, 0.24]**
Problem Type (Risky)	**0.18 [0.11, 0.24]**	**0.22 [0.13, 0.31]**	**0.11 [0.05, 0.16]**	**0.23 [0.17, 0.3]**
Problem Type (Risky) × Age Group (Older)		-0.09 [-0.22, 0.03]		**-0.26 [-0.36, -0.16]**
Problem Type (Simple Safe)	**-0.44 [-0.5, -0.37]**	**-0.51 [-0.6, -0.42]**	**-0.39 [-0.44, -0.34]**	**-0.23 [-0.3, -0.16]**
Problem Type (Simple Safe) × Age Group (Older)		**0.16 [0.03, 0.29]**		**-0.33 [-0.43, -0.23]**
α (outcome sensitivity)				
(Intercept)	**0.96 [0.91, 1.01]**	**0.93 [0.87, 0.99]**	**1.11 [1.04, 1.18]**	**1.14 [1.06, 1.21]**
Age Group (Older)	**-0.1 [-0.15, -0.04]**	-0.04 [-0.13, 0.05]	0.02 [-0.05, 0.08]	-0.03 [-0.15, 0.08]
Problem Type (Risky)	**-0.56 [-0.63, -0.5]**	**-0.61 [-0.7, -0.52]**	**-0.4 [-0.48, -0.32]**	**-0.54 [-0.65, -0.44]**
Problem Type (Risky) × Age Group (Older)		0.1 [-0.03, 0.22]		**0.29 [0.13, 0.45]**
Problem Type (Simple Safe)	**-0.24 [-0.31, -0.17]**	**-0.12 [-0.21, -0.03]**	0.06 [-0.02, 0.14]	**0.12 [0.01, 0.23]**
Problem Type (Simple Safe) × Age Group (Older)		**-0.26 [-0.38, -0.12]**		-0.13 [-0.29, 0.02]

We tested the impact of certainty—the factor highlighted by Mather et al., 2012—on the CPT parameters. In a series of Bayesian GLMs, we used the CPT parameters (ρ, γ, and α) as outcome variables. In the main effect models, we used the factors age group and problem type as fixed effects. We specified the complex safe condition as the reference condition for the factor problem type. The effect of the problem type with two risky options captures the effect of offering a safe option rather than two risky options, while reducing complexity differences. To further test whether older adults were more sensitive to the availability of a safe option than younger adults on either parameter, we calculated a second set of models that also included the interaction between age group and problem type (interaction models). The coefficients for these models are displayed in Table A.7 for Study 1 and in Table A.8 for Study 2.

First, we evaluated the results for the effect of certainty on response noise (ρ parameter). In Study 1, there was a credible positive main effect of problem type (risky) in the domain of gains, indicating that response noise was lower in the risky condition than in the complex safe condition. There were no credible main effects of problem type (risky) on the response noise parameter in the domain of losses in Study 1, and in both domains in Study 2. In Study 1, there was a credible negative interaction between problem type (risky) and age group in the domain of gains on the response noise parameter. This indicates that the decrease in response noise in the risky relative to the complex safe condition was less pronounced in older than in younger adults. The other interactions were not credible.

Table A.8: Regression Coefficients From the Regressions on CPT Parameters in Study 2. Reference Condition: Complex Safe. Reference Age Group: Older Adults

Outcome Variable (Study 2)	Gain		Loss	
Predictor	Main effect model	Interaction model	Main effect model	Interaction model
ρ (response noise)				
(Intercept)	**0.17 [0.08, 0.26]**	**0.14 [0.02, 0.26]**	**0.17 [0.12, 0.22]**	**0.11 [0.05, 0.17]**
Age Group (Older)	**-0.14 [-0.22, -0.06]**	-0.08 [-0.25, 0.1]	**-0.15 [-0.19, -0.11]**	-0.03 [-0.12, 0.06]
Problem Type (Complex Safe Zero)	**0.51 [0.4, 0.64]**	**0.44 [0.26, 0.61]**	**0.43 [0.36, 0.49]**	**0.4 [0.32, 0.49]**
Problem Type (Complex Safe Zero) × Age Group (Older)		0.16 [-0.08, 0.41]		0.04 [-0.08, 0.17]
Problem Type (Risky)	0.01 [-0.12, 0.14]	0.01 [-0.17, 0.18]	0.04 [-0.02, 0.11]	0.07 [-0.02, 0.16]
Problem Type (Risky) × Age Group (Older)		0.01 [-0.24, 0.25]		-0.05 [-0.17, 0.08]
Problem Type (Simple Safe Zero)	**1.32 [1.2, 1.45]**	**1.58 [1.4, 1.74]**	**0.72 [0.65, 0.79]**	**0.99 [0.9, 1.08]**
Problem Type (Simple Safe Zero) × Age Group (Older)		**-0.51 [-0.74, -0.26]**		**-0.56 [-0.68, -0.43]**
Problem Type (Simple Safe)	0.08 [-0.05, 0.2]	0.06 [-0.11, 0.23]	0.07 [0, 0.14]	**0.1 [0.01, 0.18]**
Problem Type (Simple Safe) × Age Group (Older)		0.04 [-0.21, 0.28]		-0.04 [-0.17, 0.08]
γ (probability weighting)				
(Intercept)	**0.74 [0.68, 0.79]**	**0.76 [0.69, 0.83]**	**0.87 [0.83, 0.92]**	**0.97 [0.92, 1.03]**
Age Group (Older)	**0.22 [0.18, 0.27]**	**0.18 [0.08, 0.28]**	**0.25 [0.22, 0.29]**	0.05 [-0.02, 0.13]
Problem Type (Complex Safe Zero)	**0.2 [0.13, 0.28]**	0.08 [-0.02, 0.18]	**0.27 [0.21, 0.33]**	-0.05 [-0.12, 0.02]
Problem Type (Complex Safe Zero) × Age Group (Older)		**0.25 [0.1, 0.38]**		**0.63 [0.53, 0.73]**
Problem Type (Risky)	**0.4 [0.33, 0.47]**	**0.34 [0.24, 0.44]**	**0.23 [0.17, 0.29]**	**0.18 [0.11, 0.26]**
Problem Type (Risky) × Age Group (Older)		0.12 [-0.02, 0.26]		0.1 [0, 0.2]
Problem Type (Simple Safe Zero)	**-0.14 [-0.21, -0.07]**	-0.1 [-0.2, 0]	0.02 [-0.04, 0.08]	**-0.18 [-0.25, -0.11]**
Problem Type (Simple Safe Zero) × Age Group (Older)		-0.08 [-0.22, 0.06]		**0.4 [0.3, 0.5]**
Problem Type (Simple Safe)	**-0.13 [-0.2, -0.06]**	-0.1 [-0.2, 0]	**-0.21 [-0.27, -0.15]**	**-0.15 [-0.22, -0.08]**
Problem Type (Simple Safe) × Age Group (Older)		-0.06 [-0.2, 0.09]		**-0.12 [-0.22, -0.02]**
α (outcome sensitivity)				
(Intercept)	**0.81 [0.76, 0.86]**	**0.68 [0.62, 0.74]**	**1.04 [0.98, 1.11]**	**0.96 [0.88, 1.04]**
Age Group (Older)	-0.01 [-0.05, 0.03]	**0.25 [0.17, 0.34]**	**0.1 [0.04, 0.15]**	**0.26 [0.15, 0.37]**
Problem Type (Complex Safe Zero)	**0.16 [0.09, 0.22]**	**0.25 [0.16, 0.33]**	**0.15 [0.07, 0.23]**	**0.15 [0.04, 0.27]**
Problem Type (Complex Safe Zero) × Age Group (Older)		**-0.19 [-0.31, -0.06]**		0 [-0.16, 0.15]
Problem Type (Risky)	**-0.55 [-0.61, -0.48]**	**-0.34 [-0.42, -0.25]**	**-0.26 [-0.34, -0.17]**	-0.01 [-0.13, 0.11]
Problem Type (Risky) × Age Group (Older)		**-0.42 [-0.55, -0.3]**		**-0.49 [-0.65, -0.33]**
Problem Type (Simple Safe Zero)	**-0.11 [-0.18, -0.05]**	**0.1 [0.01, 0.18]**	0.01 [-0.07, 0.09]	0.11 [0, 0.23]
Problem Type (Simple Safe Zero) × Age Group (Older)		**-0.42 [-0.54, -0.29]**		**-0.21 [-0.37, -0.04]**
Problem Type (Simple Safe)	**-0.18 [-0.24, -0.11]**	-0.04 [-0.12, 0.05]	**-0.14 [-0.23, -0.05]**	-0.08 [-0.2, 0.03]
Problem Type (Simple Safe) × Age Group (Older)		**-0.28 [-0.41, -0.16]**		-0.11 [-0.27, 0.05]

Next, we evaluated differences in probability weighting (γ parameter) due to the availability of a safe option. In the main effect models for both domains and in both studies, the credible and positive main effect of problem type (risky) indicates that participants showed more linear probability weighting in the condition with two risky options than in the condition with a complex safe option. That is, when a safe option was available, probability weighting was less linear, irrespective of the complexity of the safe option. This indicates an enhanced the overweighting of certainty, typically assumed to accommodate the certainty effect. Was this effect more pronounced in older adults? In Study 1, the interaction between age group and problem type (risky) was not credible for the domain of gains, but credible in the domain of losses. This indicates that in the domain of losses the effect of certainty on probability weighting that persists after controlling for complexity may be more pronounced in younger (not older) adults. That is, across all participants we find evidence for a certainty effect on probability weighting beyond the effect of complexity. Nevertheless, the results do not support Mather et al.'s (2012) notion of an *increased* certainty effect in older adults—since only one interaction was credible and pointed in the opposite direction).

Finally, we evaluated how the availability of a safe option affected outcome sensitivity (α parameter). The main effect models show a negative effect of problem type (risky) on outcome sensitivity in both domains and in both studies, indicating that participants' outcome sensitivity parameters were lower when both options were risky than when a complex safe option was available. This effect was less pronounced in older adults in both domains in Study 2 and more pronounced in older adults in the domain of losses in Study 1, indicated by credible interaction terms. This indicates that outcome sensitivity may be differently affected by the availability of a safe outcome in both age groups, but there is no consistent evidence as to the direction of this effect.

In conclusion, these results suggest that the availability of a safe option affects several aspects of decision making under risk, as reflected by CPT, even after controlling for differences in the complexity of safe and risky options.

A.5 Analysis of Decision Quality

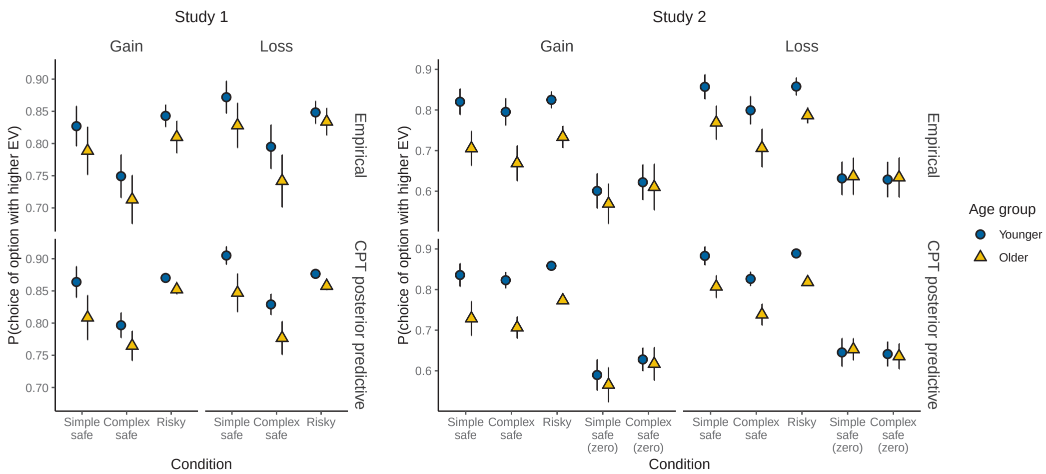

Figure A.4: Empirical and posterior predictive (i.e., predicted by CPT based on the estimated parameters) decision quality (choice proportions of the option with the higher EV) for the nondominated problems in all conditions and age groups by domain. Error bars indicate 95% confidence intervals. CPT = cumulative prospect theory.

We tested whether decision quality, that is, the tendency to choose the option with the higher EV, was associated with the manipulation of option complexity, using the data from the risky choice task of both Study 1 and Study 2. Empirical choice proportions of the higher EV option in both domains, age groups, studies, and in all conditions are displayed in Figure A.4. Figure A.4 also displays the CPT posterior predictive decision quality. As can be seen, the model reproduces the patterns observed in the data well.

We conducted Bayesian mixed-effect logistic regressions to predict the choice of the option with the higher EV, using problem type and age group (main effect model) as well as their interaction (interaction model) as fixed effects. The models further included fixed effects for the EV difference between options, a dummy variable indicating whether the option with the higher EV was also more risky, each participants' numeracy score, their self-reported risk preference and gender. The model included a random intercept for each participant. Separate models were calculated for the gain and loss domain, for each study.

We fist evaluate the main effect models: Decision quality did not differ between younger and older adults in both domains in Study 1 and in the loss domain in Study 2. Older adults' decision quality was credibly lower in the gain domain in Study 2. In both studies, decision quality was higher in participants with higher numeracy scores, and in trials with greater EV differences between the options. In the domain of gains, participants were less likely to choose the option with the higher EV if it was also the more risky option (reflecting risk aversion in the domain of gains), in both studies. In the domain of losses, participants were more likely to choose the option with the higher EV if it was also the more risky option (reflecting risk seeking in the domain of losses), in both studies. There was no main effect of gender on decision quality, in both studies. Decision quality decreased when the complexity of the safe option increased, as indicated by credible main effects of problem type (complex safe) in both domains and in both studies.

The interaction models further show that the effect of option complexity on decision quality was equally pronounced in both age groups in both studies, as indicated by the interaction effect between problem type (complex safe) and age group not being credible.

Table A.9: Regression Coefficients From the Mixed-Effects Logistic Regression of Decision Quality (Measured as Percentage Choices of the Option With the Higher EV) in the Risky Choice Task

Outcome Variable: Choice of Option with Higher EV (Study 1)	Main effect model		Interaction model	
Predictor	Gain	Loss	Gain	Loss
(Intercept)	-0.04 [-0.56, 0.44]	-0.17 [-0.67, 0.36]	-0.04 [-0.56, 0.46]	-0.12 [-0.62, 0.39]
Problem Type (Complex Safe)	**-0.55** **[-0.7, -0.4]**	**-0.62** **[-0.78, -0.47]**	**-0.59** **[-0.81, -0.37]**	**-0.65** **[-0.87, -0.42]**
Problem Type (Risky)	0.16 [0, 0.31]	-0.08 [-0.25, 0.08]	0.14 [-0.08, 0.37]	-0.22 [-0.46, 0.01]
Age Group (Older)	-0.15 [-0.4, 0.09]	-0.2 [-0.45, 0.05]	-0.18 [-0.49, 0.12]	-0.31 [-0.62, 0.02]
Higher EV Choice = Higher CV Choice	**-1.13** **[-1.26, -1]**	**0.38** **[0.25, 0.5]**	**-1.13** **[-1.26, -1]**	**0.38** **[0.24, 0.51]**
EV Difference	**0.08** **[0.07, 0.08]**	**0.06** **[0.05, 0.06]**	**0.08** **[0.07, 0.08]**	**0.06** **[0.05, 0.06]**
Numeracy	**0.34** **[0.23, 0.45]**	**0.37** **[0.26, 0.48]**	**0.34** **[0.24, 0.45]**	**0.37** **[0.26, 0.48]**
Self-reported Risk Preference	-0.01 [-0.06, 0.05]	-0.02 [-0.07, 0.04]	-0.01 [-0.06, 0.05]	-0.02 [-0.07, 0.04]
Gender (Male)	0.23 [-0.02, 0.5]	0.22 [-0.03, 0.48]	0.23 [-0.03, 0.49]	0.22 [-0.04, 0.47]
Problem Type (Complex Safe) × Age Group (Older)			0.07 [-0.22, 0.36]	0.05 [-0.25, 0.36]
Problem Type (Risky) × Age Group (Older)			0.02 [-0.29, 0.32]	0.27 [-0.05, 0.59]
Outcome Variable: Choice of Option with Higher EV (Study 2)	Main effect model		Interaction model	
Predictor	Gain	Loss	Gain	Loss
(Intercept)	**0.49** **[0.16, 0.81]**	0.11 [-0.2, 0.42]	**0.67** **[0.31, 1.01]**	0.31 [-0.02, 0.64]
Problem Type (Simple Safe Zero)	**0.19** **[0.03, 0.35]**	0.07 [-0.09, 0.23]	-0.12 [-0.33, 0.09]	**-0.28** **[-0.5, -0.06]**
Problem Type (Complex Safe)	**-0.19** **[-0.34, -0.06]**	**-0.39** **[-0.53, -0.25]**	-0.18 [-0.4, 0.03]	**-0.44** **[-0.66, -0.22]**
Problem Type (Complex Safe Zero)	**0.35** **[0.18, 0.5]**	0.05 [-0.1, 0.22]	-0.02 [-0.23, 0.19]	**-0.29** **[-0.52, -0.08]**
Problem Type (Risky)	0.11 [-0.04, 0.26]	0.07 [-0.08, 0.22]	0.04 [-0.18, 0.26]	0.01 [-0.22, 0.24]
Age Group (Older)	**-0.32** **[-0.51, -0.14]**	-0.17 [-0.34, 0.01]	**-0.67** **[-0.93, -0.39]**	**-0.54** **[-0.82, -0.28]**
Higher EV Choice = Higher CV Choice	**-1.31** **[-1.4, -1.22]**	**0.31** **[0.23, 0.39]**	**-1.31** **[-1.4, -1.23]**	**0.31** **[0.23, 0.39]**
EV Difference	**0.06** **[0.05, 0.06]**	**0.06** **[0.05, 0.06]**	**0.06** **[0.05, 0.06]**	**0.06** **[0.05, 0.06]**
Numeracy	**0.14** **[0.06, 0.22]**	**0.14** **[0.07, 0.22]**	**0.14** **[0.06, 0.22]**	**0.15** **[0.07, 0.22]**
Self-reported Risk Preference	0.04 [0, 0.08]	0 [-0.04, 0.03]	0.04 [0, 0.08]	0 [-0.04, 0.03]
Gender (Male)	**0.22** **[0.03, 0.4]**	0.01 [-0.16, 0.18]	**0.22** **[0.04, 0.4]**	0.01 [-0.15, 0.18]
Problem Type (Simple Safe Zero) × Age Group (Older)			**0.61** **[0.35, 0.88]**	**0.67** **[0.39, 0.93]**
Problem Type (Complex Safe) × Age Group (Older)			-0.02 [-0.3, 0.26]	0.08 [-0.21, 0.36]
Problem Type (Complex Safe Zero) × Age Group (Older)			**0.7** **[0.44, 0.96]**	**0.67** **[0.4, 0.93]**
Problem Type (Risky) × Age Group (Older)			0.13 [-0.15, 0.42]	0.11 [-0.2, 0.4]

A.6 Posterior Predictives for GLMER Analyses of Risk Attitude

How well did the Bayesian GLMER analyses of risky choice capture the data? A Bayesian analogue to the frequentist testing of overall model significance is inspecting posterior predictives. If posterior predictives resemble the behavioral patterns found in the data closely, a good fit can be inferred (Gabry et al., 2019). Hence, we assess fit for our GLMER analyses (cf. Table 2.4) of risky choice behavior by comparing empirical choice behavior to posterior predictive choice behavior generated from the posterior parameter estimates. Posterior predictives were generated both for the main effect models and interaction models reported in the main text, using the posterior_predict() function in rstanarm.

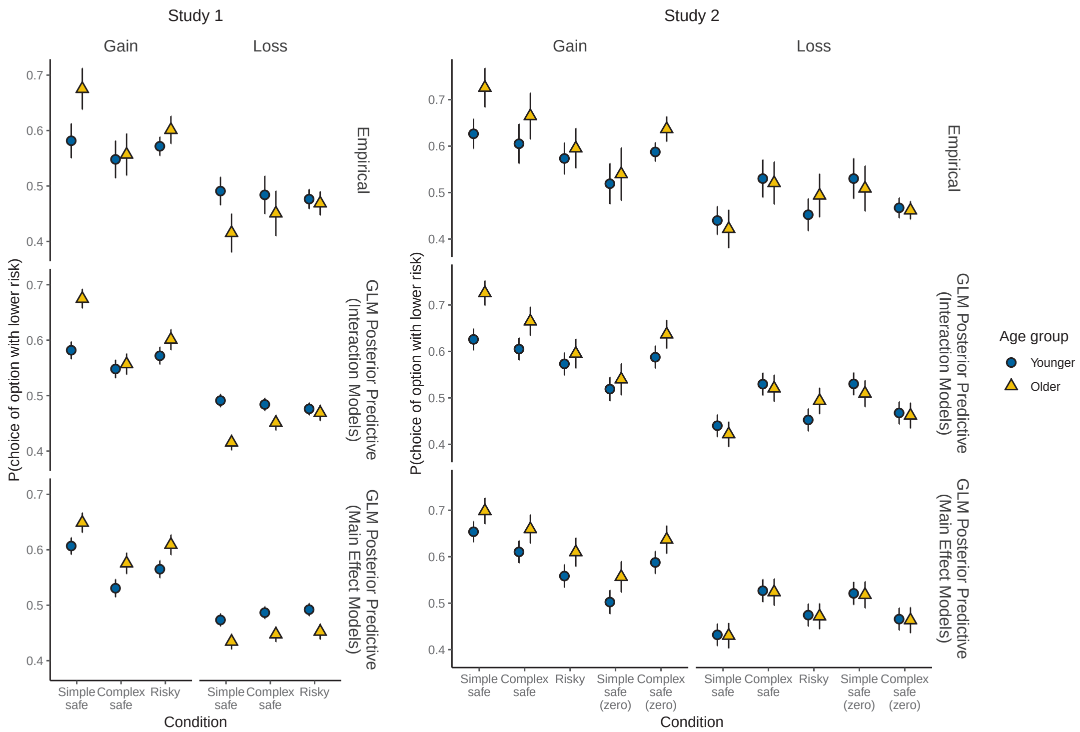

Figure A.5: Empirical and posterior predictive (i.e., predicted from the GLMERs on risk attitude based on the estimated parameters) choice proportions for the nondominated problems in all conditions and age groups by domain. Error bars indicate 95% confidence intervals.

As can be seen, the Bayesian GLMER Models for both studies and domains capture the empirical data to a high degree, indicating good fit. Comparing the posterior predictives from the main effect model (which includes fixed predictors for age group and condition, but not their interaction) to those from the interaction model (which includes the interaction between age group and condition) highlights that the interaction term crucially contributes to the models' ability to capture the key regularities found in the data. This can be interpreted as further evidence for the necessity to account for age differences in the response to option complexity.

A.7 Screenshots and Timeline for the Risky Choice Task

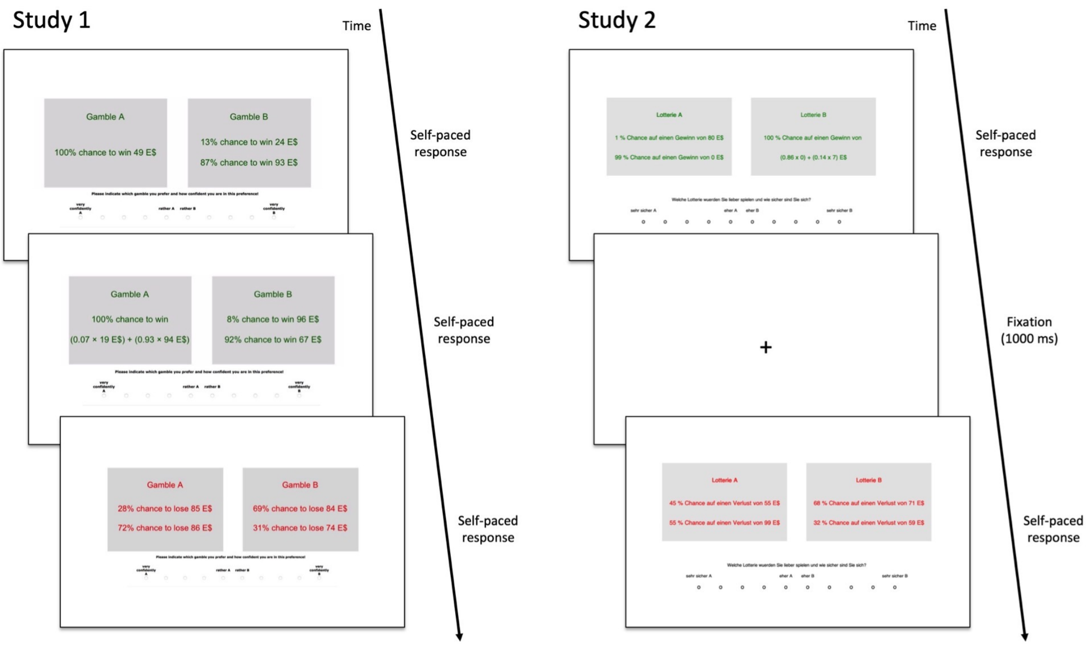

Figure A.6: Screenshots and timelines for the risky choice task in both studies. In Study 1, participants made self-paced choices with frames for individual trials immediately succeeding each other. In Study 2, individual trials were separated by a fixation period. The verbal prompt for each choice problem was “Please indicate which lottery you prefer and how confident you are in this preference” in Study 1 and the German equivalent “Welche Lotterie würden Sie lieber spielen und wie sicher sind Sie sich?” in Study 2.

Figure A.6 displays screenshots and timelines for the risky choice task in both studies. The verbal prompt for each choice problem was “Please indicate which gamble you prefer and how confident you are in this preference” in Study 1 and the German equivalent “Welche Lotterie würden Sie lieber spielen und wie sicher sind Sie sich?” in Study 2. Slight deviations in format (e.g., font, boldface) are due to programming the studies in Unipark and PsychoPy, respectively.

A.8 CPT Parameter Recovery

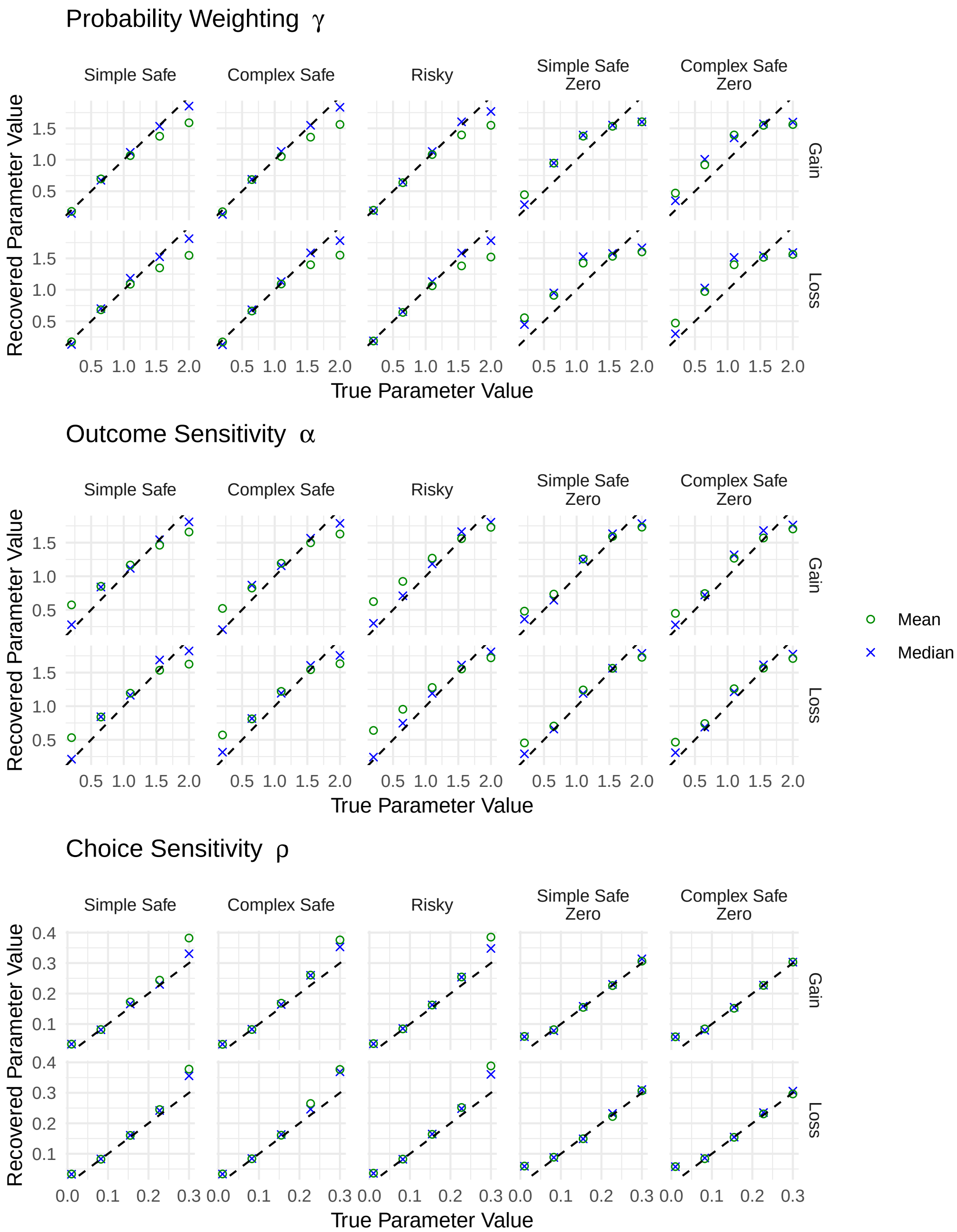

Figure A.7: Recovery of all CPT parameters for the choice problems used in the different conditions. The green points and blue crosses mark the mean and median recovered parameter value across all synthetic data. The dashed diagonal marks the parameter estimates expected under perfect parameter recovery.

To measure and disentangle different candidate mechanisms potentially underlying the effect of option complexity on age differences in risky choice, we used CPT as a computational modeling framework. In order to make valid inferences based on this approach CPT estimates need to be able to accurately distinguish the influence of the different model parameters on choice. Whether this requirement is fulfilled can be tested via parameter recovery. Several previous studies have shown that CPT parameters can be recovered robustly (Broomell & Bhatia, 2014; Glöckner et al., 2016; Kellen et al., 2016; Nilsson et al., 2011), especially when using large and diverse sets of choice problems (Broomell & Bhatia, 2014; Kellen et al., 2016) and when relying on the hierarchical Bayesian framework (Kellen et al., 2017; Nilsson et al., 2011). Both of these conditions are met in our experiments and analyses. In particular, the hierarchical Bayesian approach to estimating CPT parameters has been found preferable to maximum likelihood estimation (MLE), in recovering parameter values more accurately and with less variability (Nilsson et al., 2011; see also Murphy and ten Brincke). The hierarchical approach is particularly powerful since it exploits statistical regularities of nested experimental data: On top of the information provided by each individual it exploits population level information.

To test whether CPT parameters can also be recovered properly when our implementation of CPT is applied to the set of choice problems used in our experiments, we conducted parameter recovery analyses with this material. Specifically, we varied the three parameters of CPT within a range of reasonable settings: γ and α were varied within $[0.20, 0.65, 1.10, 1.55, 2.00]$ and ρ was varied within $[0.0100, 0.0825, 0.1550, 0.2275, 0.3000]$. The five possible settings for all three parameters were fully permuted with each other, resulting in $5 \times 5 \times 5 = 125$ parameter sets. For each parameter set, we first generated choices with CPT for 80 synthetic participants, for each of the conditions of the risky choice task of Study 2 (which include also the replicated conditions that already were part of Study 1). We then applied the same hierarchical Bayesian implementation of CPT used for the analyses presented in the main text to each of the resulting 125 simulated choice sets.

To what extent did the resulting parameter estimates recover the specific parameter values that were used to generate the choices? Figure A.7 displays the mean and median of the average individual-level recovered posterior distributions, separately for all three parameters, both domains, and five conditions. The dashed diagonal marks the parameter estimates expected under perfect parameter recovery. As can be seen, the recovered parameter values closely follow this diagonal for all parameters. This supports the adequacy of our computational modeling approach and the choice problems used to detect and disentangle the mechanisms assumed in CPT. The recovery shows that it is unlikely that the empirical choice patterns were generated by a different parameter configuration of CPT than the one identified by our modeling approach.

A.9 Choice Proportions by Problem

Table A.10: Individual Choice Problems and Proportions of the Risky Option in Younger and Older Adults for Study 1 (Gains). Choice proportion of the Risky Option in Younger adults: %risky YA. Choice proportion of the Risky Option in Older adults: %risky OA

pA1	pA2	oA1	oA2	pB1	pB2	oB1	oB2	oB1 (formatted)	Condition	Domain	%risky YA	%risky OA
0.02	0.98	98	57	1.00	0.00	91	0.00	(0.7 97) + (0.377)	Complex Safe	gain	0.07	0.22
0.03	0.97	51	88	1.00	0.00	67	0.00	(0.07 91) + (0.9365)	Complex Safe	gain	0.79	0.74
0.03	0.97	92	70	1.00	0.00	91	0.00	(0.81 99) + (0.1957)	Complex Safe	gain	0.22	0.16
0.16	0.84	23	97	1.00	0.00	55	0.00	(0.12 17) + (0.8860)	Complex Safe	gain	0.83	0.70
0.17	0.83	13	72	1.00	0.00	37	0.00	(0.96 35) + (0.0485)	Complex Safe	gain	0.77	0.72
0.17	0.83	96	37	1.00	0.00	82	0.00	(0.08 52) + (0.9285)	Complex Safe	gain	0.06	0.08
0.18	0.82	96	34	1.00	0.00	51	0.00	(0.38 12) + (0.6275)	Complex Safe	gain	0.50	0.54
0.19	0.81	25	95	1.00	0.00	47	0.00	(0.03 49) + (0.9747)	Complex Safe	gain	0.82	0.75
0.39	0.61	79	20	1.00	0.00	52	0.00	(0.44 71) + (0.5637)	Complex Safe	gain	0.07	0.16
0.43	0.57	77	79	1.00	0.00	75	0.00	(0.03 53) + (0.9776)	Complex Safe	gain	0.66	0.58
0.45	0.55	53	97	1.00	0.00	65	0.00	(0.68 69) + (0.3257)	Complex Safe	gain	0.65	0.62
0.45	0.55	66	17	1.00	0.00	64	0.00	(0.68 67) + (0.3258)	Complex Safe	gain	0.07	0.07
0.46	0.54	4	85	1.00	0.00	39	0.00	(0.67 21) + (0.3376)	Complex Safe	gain	0.39	0.33
0.47	0.53	43	85	1.00	0.00	77	0.00	(0.04 19) + (0.9679)	Complex Safe	gain	0.48	0.45
0.72	0.28	64	68	1.00	0.00	60	0.00	(0.16 57) + (0.8461)	Complex Safe	gain	0.78	0.66
0.73	0.27	39	83	1.00	0.00	45	0.00	(0.74 59) + (0.265)	Complex Safe	gain	0.51	0.53
0.77	0.23	40	97	1.00	0.00	83	0.00	(0.22 78) + (0.7884)	Complex Safe	gain	0.15	0.17
0.91	0.09	94	38	1.00	0.00	56	0.00	(0.27 5) + (0.7375)	Complex Safe	gain	0.85	0.87
0.02	0.98	96	55	0.70	0.30	95	75.00	0	Risky	gain	0.89	0.91
0.03	0.97	53	90	0.07	0.93	93	67.00	0	Risky	gain	0.06	0.04
0.03	0.97	88	66	0.81	0.19	95	53.00	0	Risky	gain	0.84	0.72
0.16	0.84	19	93	0.12	0.88	13	56.00	0	Risky	gain	0.99	0.99
0.17	0.83	11	70	0.96	0.04	33	83.00	0	Risky	gain	0.88	0.76
0.17	0.83	98	39	0.08	0.92	54	87.00	0	Risky	gain	0.04	0.05
0.18	0.82	94	32	0.38	0.62	10	73.00	0	Risky	gain	0.59	0.50
0.19	0.81	23	93	0.03	0.97	47	45.00	0	Risky	gain	0.87	0.79
0.39	0.61	77	18	0.44	0.56	69	35.00	0	Risky	gain	0.10	0.11
0.43	0.57	75	77	0.03	0.97	51	74.00	0	Risky	gain	0.32	0.39
0.45	0.55	55	99	0.68	0.32	71	59.00	0	Risky	gain	0.77	0.64
0.45	0.55	64	15	0.68	0.32	65	56.00	0	Risky	gain	0.01	0.03
0.46	0.54	6	87	0.67	0.33	23	78.00	0	Risky	gain	0.35	0.36
0.47	0.53	45	87	0.04	0.96	21	81.00	0	Risky	gain	0.22	0.17
0.72	0.28	66	70	0.16	0.84	59	63.00	0	Risky	gain	0.84	0.80
0.73	0.27	35	79	0.74	0.26	55	1.00	0	Risky	gain	0.18	0.25
0.77	0.23	42	99	0.22	0.78	80	86.00	0	Risky	gain	0.06	0.07
0.91	0.09	96	40	0.27	0.73	7	77.00	0	Risky	gain	0.01	0.00
0.02	0.98	100	59	1.00	0.00	93	0.00	0	Simple Safe	gain	0.01	0.00
0.03	0.97	55	92	1.00	0.00	71	0.00	0	Simple Safe	gain	0.82	0.75
0.03	0.97	90	68	1.00	0.00	89	0.00	0	Simple Safe	gain	0.02	0.00
0.16	0.84	21	95	1.00	0.00	53	0.00	0	Simple Safe	gain	0.83	0.71
0.17	0.83	15	74	1.00	0.00	39	0.00	0	Simple Safe	gain	0.80	0.75
0.17	0.83	94	35	1.00	0.00	80	0.00	0	Simple Safe	gain	0.04	0.00
0.18	0.82	92	30	1.00	0.00	47	0.00	0	Simple Safe	gain	0.38	0.17
0.19	0.81	27	97	1.00	0.00	49	0.00	0	Simple Safe	gain	0.84	0.67
0.39	0.61	75	16	1.00	0.00	48	0.00	0	Simple Safe	gain	0.18	0.08
0.43	0.57	73	75	1.00	0.00	71	0.00	0	Simple Safe	gain	0.73	0.66
0.45	0.55	51	95	1.00	0.00	63	0.00	0	Simple Safe	gain	0.76	0.53
0.45	0.55	62	13	1.00	0.00	60	0.00	0	Simple Safe	gain	0.05	0.00
0.46	0.54	8	89	1.00	0.00	43	0.00	0	Simple Safe	gain	0.32	0.21
0.47	0.53	41	83	1.00	0.00	75	0.00	0	Simple Safe	gain	0.02	0.03
0.72	0.28	68	72	1.00	0.00	64	0.00	0	Simple Safe	gain	0.68	0.58
0.73	0.27	37	81	1.00	0.00	43	0.00	0	Simple Safe	gain	0.71	0.49
0.77	0.23	38	95	1.00	0.00	81	0.00	0	Simple Safe	gain	0.02	0.01
0.91	0.09	98	42	1.00	0.00	60	0.00	0	Simple Safe	gain	0.89	0.80

Table A.11: Individual Choice Problems and Proportions of the Risky Option in Younger and Older Adults for Study 1 (Losses). Choice proportion of the Risky Option in Younger adults: %risky YA. Choice proportion of the Risky Option in Older adults: %risky OA

pA1	pA2	oA1	oA2	pB1	pB2	oB1	oB2	oB1 (formatted)	Condition	Domain	%risky YA	%risky OA
0.02	0.98	-100	-59	1.00	0.00	-93	0.00	(0.7 99) + (0.379)	Complex Safe	loss	0.84	0.78
0.03	0.97	-92	-70	1.00	0.00	-91	0.00	(0.81 99) + (0.1957)	Complex Safe	loss	0.85	0.82
0.03	0.97	-51	-88	1.00	0.00	-67	0.00	(0.07 91) + (0.9365)	Complex Safe	loss	0.16	0.20
0.16	0.84	-21	-95	1.00	0.00	-53	0.00	(0.12 15) + (0.8858)	Complex Safe	loss	0.15	0.22
0.17	0.83	-94	-35	1.00	0.00	-80	0.00	(0.08 50) + (0.9283)	Complex Safe	loss	0.89	0.88
0.17	0.83	-13	-72	1.00	0.00	-37	0.00	(0.96 35) + (0.0485)	Complex Safe	loss	0.21	0.29
0.18	0.82	-96	-34	1.00	0.00	-51	0.00	(0.38 12) + (0.6275)	Complex Safe	loss	0.68	0.68
0.19	0.81	-27	-97	1.00	0.00	-49	0.00	(0.03 51) + (0.9749)	Complex Safe	loss	0.10	0.28
0.39	0.61	-79	-20	1.00	0.00	-52	0.00	(0.44 71) + (0.5637)	Complex Safe	loss	0.79	0.80
0.44	0.56	-72	-70	1.00	0.00	-74	0.00	(0.46 73) + (0.5475)	Complex Safe	loss	0.74	0.75
0.45	0.55	-62	-13	1.00	0.00	-60	0.00	(0.68 63) + (0.3254)	Complex Safe	loss	0.89	0.88
0.45	0.55	-53	-97	1.00	0.00	-65	0.00	(0.68 69) + (0.3257)	Complex Safe	loss	0.28	0.30
0.46	0.54	-4	-85	1.00	0.00	-39	0.00	(0.67 21) + (0.3376)	Complex Safe	loss	0.48	0.50
0.47	0.53	-41	-83	1.00	0.00	-75	0.00	(0.04 17) + (0.9677)	Complex Safe	loss	0.78	0.76
0.68	0.32	-66	-60	1.00	0.00	-69	0.00	(0.02 67) + (0.9869)	Complex Safe	loss	0.80	0.82
0.73	0.27	-35	-79	1.00	0.00	-41	0.00	(0.74 55) + (0.261)	Complex Safe	loss	0.30	0.46
0.77	0.23	-42	-99	1.00	0.00	-85	0.00	(0.22 80) + (0.7886)	Complex Safe	loss	0.76	0.72
0.91	0.09	-96	-40	1.00	0.00	-58	0.00	(0.27 7) + (0.7377)	Complex Safe	loss	0.10	0.21
0.02	0.98	-98	-57	0.70	0.30	-97	-77.00	0	Risky	loss	0.09	0.11
0.03	0.97	-88	-66	0.81	0.19	-95	-53.00	0	Risky	loss	0.12	0.24
0.03	0.97	-53	-90	0.07	0.93	-93	-67.00	0	Risky	loss	0.89	0.86
0.16	0.84	-23	-97	0.12	0.88	-17	-60.00	0	Risky	loss	0.04	0.01
0.17	0.83	-96	-37	0.08	0.92	-52	-85.00	0	Risky	loss	0.91	0.91
0.17	0.83	-11	-70	0.96	0.04	-33	-83.00	0	Risky	loss	0.12	0.11
0.18	0.82	-92	-30	0.38	0.62	-8	-71.00	0	Risky	loss	0.40	0.38
0.19	0.81	-25	-95	0.03	0.97	-49	-47.00	0	Risky	loss	0.04	0.11
0.39	0.61	-75	-16	0.44	0.56	-67	-33.00	0	Risky	loss	0.82	0.80
0.44	0.56	-74	-72	0.46	0.54	-75	-77.00	0	Risky	loss	0.94	0.91
0.45	0.55	-64	-15	0.68	0.32	-65	-56.00	0	Risky	loss	0.93	0.95
0.45	0.55	-55	-99	0.68	0.32	-71	-59.00	0	Risky	loss	0.21	0.16
0.46	0.54	-8	-89	0.67	0.33	-25	-80.00	0	Risky	loss	0.39	0.47
0.47	0.53	-45	-87	0.04	0.96	-21	-81.00	0	Risky	loss	0.85	0.87
0.68	0.32	-62	-56	0.02	0.98	-63	-65.00	0	Risky	loss	0.93	0.92
0.73	0.27	-37	-81	0.74	0.26	-57	-3.00	0	Risky	loss	0.72	0.67
0.77	0.23	-40	-97	0.22	0.78	-78	-84.00	0	Risky	loss	0.90	0.87
0.91	0.09	-94	-38	0.27	0.73	-5	-75.00	0	Risky	loss	0.95	1.00
0.02	0.98	-96	-55	1.00	0.00	-89	0.00	0	Simple Safe	loss	0.96	0.93
0.03	0.97	-90	-68	1.00	0.00	-89	0.00	0	Simple Safe	loss	0.98	1.00
0.03	0.97	-55	-92	1.00	0.00	-71	0.00	0	Simple Safe	loss	0.10	0.17
0.16	0.84	-19	-93	1.00	0.00	-51	0.00	0	Simple Safe	loss	0.06	0.18
0.17	0.83	-98	-39	1.00	0.00	-84	0.00	0	Simple Safe	loss	0.95	0.97
0.17	0.83	-15	-74	1.00	0.00	-39	0.00	0	Simple Safe	loss	0.11	0.28
0.18	0.82	-94	-32	1.00	0.00	-49	0.00	0	Simple Safe	loss	0.55	0.62
0.19	0.81	-23	-93	1.00	0.00	-45	0.00	0	Simple Safe	loss	0.13	0.21
0.39	0.61	-77	-18	1.00	0.00	-50	0.00	0	Simple Safe	loss	0.84	0.91
0.44	0.56	-76	-74	1.00	0.00	-78	0.00	0	Simple Safe	loss	0.95	0.97
0.45	0.55	-66	-17	1.00	0.00	-64	0.00	0	Simple Safe	loss	0.98	0.97
0.45	0.55	-51	-95	1.00	0.00	-63	0.00	0	Simple Safe	loss	0.11	0.25
0.46	0.54	-6	-87	1.00	0.00	-41	0.00	0	Simple Safe	loss	0.30	0.47
0.47	0.53	-43	-85	1.00	0.00	-77	0.00	0	Simple Safe	loss	0.83	0.95
0.68	0.32	-64	-58	1.00	0.00	-67	0.00	0	Simple Safe	loss	0.90	0.92
0.73	0.27	-39	-83	1.00	0.00	-45	0.00	0	Simple Safe	loss	0.20	0.34
0.77	0.23	-38	-95	1.00	0.00	-81	0.00	0	Simple Safe	loss	0.96	0.95
0.91	0.09	-98	-42	1.00	0.00	-60	0.00	0	Simple Safe	loss	0.09	0.14

Table A.12: Individual Choice Problems and Proportions of the Risky Option in Younger and Older Adults for Study 2 (Gains). Choice proportion of the Risky Option in Younger adults: %risky YA. Choice proportion of the Risky Option in Older adults: %risky OA

pA1	pA2	oA1	oA2	pB1	pB2	oB1	oB2	oB1 (formatted)	Condition	Domain	%risky YA	%risky OA
0.02	0.98	98.00	57	1.00	0.00	91.00	0.00	(0.7 x 97) + (0.3 x 77)	Complex Safe	gain	0.17	0.28
0.03	0.97	51.00	88	1.00	0.00	66.82	0.00	(0.07 x 91) + (0.93 x 65)	Complex Safe	gain	0.85	0.64
0.03	0.97	92.00	70	1.00	0.00	91.02	0.00	(0.81 x 99) + (0.19 x 57)	Complex Safe	gain	0.09	0.24
0.16	0.84	23.00	97	1.00	0.00	54.84	0.00	(0.12 x 17) + (0.88 x 60)	Complex Safe	gain	0.72	0.59
0.17	0.83	13.00	72	1.00	0.00	37.00	0.00	(0.96 x 35) + (0.04 x 85)	Complex Safe	gain	0.85	0.64
0.17	0.83	96.00	37	1.00	0.00	82.36	0.00	(0.08 x 52) + (0.92 x 85)	Complex Safe	gain	0.05	0.20
0.18	0.82	96.00	34	1.00	0.00	51.06	0.00	(0.38 x 12) + (0.62 x 75)	Complex Safe	gain	0.34	0.39
0.19	0.81	25.00	95	1.00	0.00	47.06	0.00	(0.03 x 49) + (0.97 x 47)	Complex Safe	gain	0.81	0.68
0.39	0.61	79.00	20	1.00	0.00	51.96	0.00	(0.44 x 71) + (0.56 x 37)	Complex Safe	gain	0.15	0.24
0.43	0.56	77.00	79	1.00	0.00	75.31	0.00	(0.03 x 53) + (0.97 x 76)	Complex Safe	gain	0.70	0.42
0.45	0.55	53.00	97	1.00	0.00	65.16	0.00	(0.68 x 69) + (0.32 x 57)	Complex Safe	gain	0.70	0.45
0.45	0.55	66.00	17	1.00	0.00	64.12	0.00	(0.68 x 67) + (0.32 x 58)	Complex Safe	gain	0.03	0.12
0.46	0.54	4.00	85	1.00	0.00	39.15	0.00	(0.67 x 21) + (0.33 x 76)	Complex Safe	gain	0.30	0.33
0.47	0.53	43.00	85	1.00	0.00	76.60	0.00	(0.04 x 19) + (0.96 x 79)	Complex Safe	gain	0.12	0.21
0.72	0.28	64.00	68	1.00	0.00	60.36	0.00	(0.16 x 57) + (0.84 x 61)	Complex Safe	gain	0.84	0.57
0.73	0.27	39.00	83	1.00	0.00	44.96	0.00	(0.74 x 59) + (0.26 x 5)	Complex Safe	gain	0.62	0.53
0.77	0.23	40.00	97	1.00	0.00	82.68	0.00	(0.22 x 78) + (0.78 x 84)	Complex Safe	gain	0.10	0.21
0.91	0.09	94.00	38	1.00	0.00	56.10	0.00	(0.27 x 5) + (0.73 x 75)	Complex Safe	gain	0.91	0.75
0.01	0.99	80.00	0	1.00	0.00	0.98	0.00	(0.86 x 0) + (0.14 x 7)	Complex Safe Zero	gain	0.56	0.40
0.01	0.99	100.00	0	1.00	0.00	0.84	0.00	(0.58 x 0) + (0.42 x 2)	Complex Safe Zero	gain	0.62	0.51
0.05	0.95	16.00	0	1.00	0.00	0.95	0.00	(0.81 x 0) + (0.19 x 5)	Complex Safe Zero	gain	0.45	0.44
0.05	0.95	20.00	0	1.00	0.00	0.75	0.00	(0.85 x 0) + (0.15 x 5)	Complex Safe Zero	gain	0.62	0.49
0.10	0.90	8.00	0	1.00	0.00	0.97	0.00	(0.03 x 0) + (0.97 x 1)	Complex Safe Zero	gain	0.68	0.56
0.10	0.90	10.00	0	1.00	0.00	0.80	0.00	(0.6 x 0) + (0.4 x 2)	Complex Safe Zero	gain	0.71	0.61
0.20	0.80	50.00	0	1.00	0.00	12.48	0.00	(0.74 x 0) + (0.26 x 48)	Complex Safe Zero	gain	0.21	0.21
0.20	0.80	62.50	0	1.00	0.00	10.01	0.00	(0.09 x 0) + (0.91 x 11)	Complex Safe Zero	gain	0.49	0.40
0.40	0.60	25.00	0	1.00	0.00	12.48	0.00	(0.61 x 0) + (0.39 x 32)	Complex Safe Zero	gain	0.12	0.24
0.40	0.60	31.25	0	1.00	0.00	10.00	0.00	(0.98 x 0) + (0.02 x 500)	Complex Safe Zero	gain	0.49	0.41
0.60	0.40	16.67	0	1.00	0.00	12.46	0.00	(0.86 x 0) + (0.14 x 89)	Complex Safe Zero	gain	0.21	0.26
0.60	0.40	20.83	0	1.00	0.00	9.96	0.00	(0.17 x 0) + (0.83 x 12)	Complex Safe Zero	gain	0.51	0.50
0.80	0.20	12.50	0	1.00	0.00	12.50	0.00	(0.75 x 0) + (0.25 x 50)	Complex Safe Zero	gain	0.06	0.11
0.80	0.20	15.62	0	1.00	0.00	10.00	0.00	(0.9 x 0) + (0.1 x 100)	Complex Safe Zero	gain	0.57	0.59
0.90	0.10	11.11	0	1.00	0.00	12.50	0.00	(0.98 x 0) + (0.02 x 625)	Complex Safe Zero	gain	0.20	0.25
0.90	0.10	13.89	0	1.00	0.00	9.99	0.00	(0.63 x 0) + (0.37 x 27)	Complex Safe Zero	gain	0.59	0.68
0.95	0.05	10.53	0	1.00	0.00	12.53	0.00	(0.93 x 0) + (0.07 x 179)	Complex Safe Zero	gain	0.25	0.29
0.95	0.05	13.16	0	1.00	0.00	10.01	0.00	(0.09 x 0) + (0.91 x 11)	Complex Safe Zero	gain	0.56	0.64
0.99	0.01	10.10	0	1.00	0.00	12.47	0.00	(0.57 x 0) + (0.43 x 29)	Complex Safe Zero	gain	0.14	0.24
0.99	0.01	12.63	0	1.00	0.00	10.01	0.00	(0.23 x 0) + (0.77 x 13)	Complex Safe Zero	gain	0.70	0.78
0.02	0.98	96.00	55	0.70	0.30	95.00	75.00	95	Risky	gain	0.95	0.64
0.03	0.97	53.00	90	0.07	0.93	93.00	67.00	93	Risky	gain	0.09	0.15
0.03	0.97	88.00	66	0.81	0.19	95.00	53.00	95	Risky	gain	0.82	0.59
0.16	0.84	19.00	93	0.12	0.88	13.00	56.00	13	Risky	gain	0.96	0.85
0.17	0.83	11.00	70	0.96	0.04	33.00	83.00	33	Risky	gain	0.81	0.66
0.17	0.83	98.00	39	0.08	0.92	54.00	87.00	54	Risky	gain	0.00	0.04
0.18	0.82	94.00	32	0.38	0.62	10.00	73.00	10	Risky	gain	0.47	0.36
0.19	0.81	23.00	93	0.03	0.97	47.00	45.00	47	Risky	gain	0.88	0.68
0.39	0.61	77.00	18	0.44	0.56	69.00	35.00	69	Risky	gain	0.05	0.10
0.43	0.56	75.00	77	0.03	0.97	51.00	74.00	51	Risky	gain	0.19	0.46
0.45	0.55	55.00	99	0.68	0.32	71.00	59.00	71	Risky	gain	0.71	0.65
0.45	0.55	64.00	15	0.68	0.32	65.00	56.00	65	Risky	gain	0.01	0.05
0.46	0.54	6.00	87	0.67	0.33	23.00	78.00	23	Risky	gain	0.29	0.35
0.47	0.53	45.00	87	0.04	0.96	21.00	81.00	21	Risky	gain	0.39	0.26
0.72	0.28	66.00	70	0.16	0.84	59.00	63.00	59	Risky	gain	0.91	0.64
0.73	0.27	35.00	79	0.74	0.26	55.00	1.00	55	Risky	gain	0.16	0.31
0.77	0.23	42.00	99	0.22	0.78	80.00	86.00	80	Risky	gain	0.00	0.07
0.91	0.09	96.00	40	0.27	0.73	7.00	77.00	7	Risky	gain	0.00	0.05
0.02	0.98	100.00	59	1.00	0.00	93.00	0.00	93	Simple Safe	gain	0.00	0.03
0.03	0.97	55.00	92	1.00	0.00	71.00	0.00	71	Simple Safe	gain	0.78	0.65
0.03	0.97	90.00	68	1.00	0.00	89.00	0.00	89	Simple Safe	gain	0.01	0.05
0.16	0.84	21.00	95	1.00	0.00	53.00	0.00	53	Simple Safe	gain	0.68	0.51
0.17	0.83	15.00	74	1.00	0.00	39.00	0.00	39	Simple Safe	gain	0.74	0.60
0.17	0.83	94.00	35	1.00	0.00	80.00	0.00	80	Simple Safe	gain	0.01	0.04
0.18	0.82	92.00	30	1.00	0.00	47.00	0.00	47	Simple Safe	gain	0.29	0.23
0.19	0.81	27.00	97	1.00	0.00	49.00	0.00	49	Simple Safe	gain	0.78	0.50
0.39	0.61	75.00	16	1.00	0.00	48.00	0.00	48	Simple Safe	gain	0.07	0.07
0.43	0.56	73.00	75	1.00	0.00	71.00	0.00	71	Simple Safe	gain	0.76	0.47
0.45	0.55	51.00	95	1.00	0.00	63.00	0.00	63	Simple Safe	gain	0.79	0.42
0.45	0.55	62.00	13	1.00	0.00	60.00	0.00	60	Simple Safe	gain	0.01	0.03
0.46	0.54	8.00	89	1.00	0.00	43.00	0.00	43	Simple Safe	gain	0.25	0.19
0.47	0.53	41.00	83	1.00	0.00	75.00	0.00	75	Simple Safe	gain	0.03	0.09
0.72	0.28	68.00	72	1.00	0.00	64.00	0.00	64	Simple Safe	gain	0.82	0.46
0.73	0.27	37.00	81	1.00	0.00	43.00	0.00	43	Simple Safe	gain	0.68	0.39
0.77	0.23	38.00	95	1.00	0.00	81.00	0.00	81	Simple Safe	gain	0.00	0.03
0.91	0.09	98.00	42	1.00	0.00	60.00	0.00	60	Simple Safe	gain	0.88	0.57
0.01	0.99	80.00	0	1.00	0.00	1.00	0.00	1	Simple Safe Zero	gain	0.53	0.36
0.01	0.99	100.00	0	1.00	0.00	0.80	0.00	0.8	Simple Safe Zero	gain	0.69	0.38
0.05	0.95	16.00	0	1.00	0.00	1.00	0.00	1	Simple Safe Zero	gain	0.50	0.39
0.05	0.95	20.00	0	1.00	0.00	0.80	0.00	0.8	Simple Safe Zero	gain	0.74	0.49
0.10	0.90	8.00	0	1.00	0.00	1.00	0.00	1	Simple Safe Zero	gain	0.51	0.35
0.10	0.90	10.00	0	1.00	0.00	0.80	0.00	0.8	Simple Safe Zero	gain	0.64	0.49
0.20	0.80	50.00	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.10	0.20
0.20	0.80	62.50	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.40	0.30
0.40	0.60	25.00	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.07	0.10
0.40	0.60	31.25	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.42	0.33
0.60	0.40	16.67	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.04	0.06
0.60	0.40	20.83	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.34	0.33
0.80	0.20	12.50	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.00	0.05
0.80	0.20	15.62	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.38	0.41
0.90	0.10	11.11	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.00	0.04
0.90	0.10	13.89	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.31	0.38
0.95	0.05	10.53	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.00	0.05
0.95	0.05	13.16	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.42	0.38
0.99	0.01	10.10	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.04	0.03
0.99	0.01	12.63	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.62	0.72

Table A.13: Individual Choice Problems and Proportions of the Risky Option in Younger and Older Adults for Study 2 (Losses). Choice proportion of the Risky Option in Younger adults: %risky YA. Choice proportion of the Risky Option in Older adults: %risky OA

pA1	pA2	oA1	oA2	pB1	pB2	oB1	oB2	oB1 (formatted)	Condition	Domain	%risky YA	%risky OA
0.02	0.98	98.00	57	1.00	0.00	91.00	0.00	(0.7 x 97) + (0.3 x 77)	Complex Safe	gain	0.17	0.28
0.03	0.97	51.00	88	1.00	0.00	66.82	0.00	(0.07 x 91) + (0.93 x 65)	Complex Safe	gain	0.85	0.64
0.03	0.97	92.00	70	1.00	0.00	91.02	0.00	(0.81 x 99) + (0.19 x 57)	Complex Safe	gain	0.09	0.24
0.16	0.84	23.00	97	1.00	0.00	54.84	0.00	(0.12 x 17) + (0.88 x 60)	Complex Safe	gain	0.72	0.59
0.17	0.83	13.00	72	1.00	0.00	37.00	0.00	(0.96 x 35) + (0.04 x 85)	Complex Safe	gain	0.85	0.64
0.17	0.83	96.00	37	1.00	0.00	82.36	0.00	(0.08 x 52) + (0.92 x 85)	Complex Safe	gain	0.05	0.20
0.18	0.82	96.00	34	1.00	0.00	51.06	0.00	(0.38 x 12) + (0.62 x 75)	Complex Safe	gain	0.34	0.39
0.19	0.81	25.00	95	1.00	0.00	47.06	0.00	(0.03 x 49) + (0.97 x 47)	Complex Safe	gain	0.81	0.68
0.39	0.61	79.00	20	1.00	0.00	51.96	0.00	(0.44 x 71) + (0.56 x 37)	Complex Safe	gain	0.15	0.24
0.43	0.56	77.00	79	1.00	0.00	75.31	0.00	(0.03 x 53) + (0.97 x 76)	Complex Safe	gain	0.70	0.42
0.45	0.55	53.00	97	1.00	0.00	65.16	0.00	(0.68 x 69) + (0.32 x 57)	Complex Safe	gain	0.70	0.45
0.45	0.55	66.00	17	1.00	0.00	64.12	0.00	(0.68 x 67) + (0.32 x 58)	Complex Safe	gain	0.03	0.12
0.46	0.54	4.00	85	1.00	0.00	39.15	0.00	(0.67 x 21) + (0.33 x 76)	Complex Safe	gain	0.30	0.33
0.47	0.53	43.00	85	1.00	0.00	76.60	0.00	(0.04 x 19) + (0.96 x 79)	Complex Safe	gain	0.12	0.21
0.72	0.28	64.00	68	1.00	0.00	60.36	0.00	(0.16 x 57) + (0.84 x 61)	Complex Safe	gain	0.84	0.57
0.73	0.27	39.00	83	1.00	0.00	44.96	0.00	(0.74 x 59) + (0.26 x 5)	Complex Safe	gain	0.62	0.53
0.77	0.23	40.00	97	1.00	0.00	82.68	0.00	(0.22 x 78) + (0.78 x 84)	Complex Safe	gain	0.10	0.21
0.91	0.09	94.00	38	1.00	0.00	56.10	0.00	(0.27 x 5) + (0.73 x 75)	Complex Safe	gain	0.91	0.75
0.01	0.99	80.00	0	1.00	0.00	0.98	0.00	(0.86 x 0) + (0.14 x 7)	Complex Safe Zero	gain	0.56	0.40
0.01	0.99	100.00	0	1.00	0.00	0.84	0.00	(0.58 x 0) + (0.42 x 2)	Complex Safe Zero	gain	0.62	0.51
0.05	0.95	16.00	0	1.00	0.00	0.95	0.00	(0.81 x 0) + (0.19 x 5)	Complex Safe Zero	gain	0.45	0.44
0.05	0.95	20.00	0	1.00	0.00	0.75	0.00	(0.85 x 0) + (0.15 x 5)	Complex Safe Zero	gain	0.62	0.49
0.10	0.90	8.00	0	1.00	0.00	0.97	0.00	(0.03 x 0) + (0.97 x 1)	Complex Safe Zero	gain	0.68	0.56
0.10	0.90	10.00	0	1.00	0.00	0.80	0.00	(0.6 x 0) + (0.4 x 2)	Complex Safe Zero	gain	0.71	0.61
0.20	0.80	50.00	0	1.00	0.00	12.48	0.00	(0.74 x 0) + (0.26 x 48)	Complex Safe Zero	gain	0.21	0.21
0.20	0.80	62.50	0	1.00	0.00	10.01	0.00	(0.09 x 0) + (0.91 x 11)	Complex Safe Zero	gain	0.49	0.40
0.40	0.60	25.00	0	1.00	0.00	12.48	0.00	(0.61 x 0) + (0.39 x 32)	Complex Safe Zero	gain	0.12	0.24
0.40	0.60	31.25	0	1.00	0.00	10.00	0.00	(0.98 x 0) + (0.02 x 500)	Complex Safe Zero	gain	0.49	0.41
0.60	0.40	16.67	0	1.00	0.00	12.46	0.00	(0.86 x 0) + (0.14 x 89)	Complex Safe Zero	gain	0.21	0.26
0.60	0.40	20.83	0	1.00	0.00	9.96	0.00	(0.17 x 0) + (0.83 x 12)	Complex Safe Zero	gain	0.51	0.50
0.80	0.20	12.50	0	1.00	0.00	12.50	0.00	(0.75 x 0) + (0.25 x 50)	Complex Safe Zero	gain	0.06	0.11
0.80	0.20	15.62	0	1.00	0.00	10.00	0.00	(0.9 x 0) + (0.1 x 100)	Complex Safe Zero	gain	0.57	0.59
0.90	0.10	11.11	0	1.00	0.00	12.50	0.00	(0.98 x 0) + (0.02 x 625)	Complex Safe Zero	gain	0.20	0.25
0.90	0.10	13.89	0	1.00	0.00	9.99	0.00	(0.63 x 0) + (0.37 x 27)	Complex Safe Zero	gain	0.59	0.68
0.95	0.05	10.53	0	1.00	0.00	12.53	0.00	(0.93 x 0) + (0.07 x 179)	Complex Safe Zero	gain	0.25	0.29
0.95	0.05	13.16	0	1.00	0.00	10.01	0.00	(0.09 x 0) + (0.91 x 11)	Complex Safe Zero	gain	0.56	0.64
0.99	0.01	10.10	0	1.00	0.00	12.47	0.00	(0.57 x 0) + (0.43 x 29)	Complex Safe Zero	gain	0.14	0.24
0.99	0.01	12.63	0	1.00	0.00	10.01	0.00	(0.23 x 0) + (0.77 x 13)	Complex Safe Zero	gain	0.70	0.78
0.02	0.98	96.00	55	0.70	0.30	95.00	75.00	95	Risky	gain	0.95	0.64
0.03	0.97	53.00	90	0.07	0.93	93.00	67.00	93	Risky	gain	0.09	0.15
0.03	0.97	88.00	66	0.81	0.19	95.00	53.00	95	Risky	gain	0.82	0.59
0.16	0.84	19.00	93	0.12	0.88	13.00	56.00	13	Risky	gain	0.96	0.85
0.17	0.83	11.00	70	0.96	0.04	33.00	83.00	33	Risky	gain	0.81	0.66
0.17	0.83	98.00	39	0.08	0.92	54.00	87.00	54	Risky	gain	0.00	0.04
0.18	0.82	94.00	32	0.38	0.62	10.00	73.00	10	Risky	gain	0.47	0.36
0.19	0.81	23.00	93	0.03	0.97	47.00	45.00	47	Risky	gain	0.88	0.68
0.39	0.61	77.00	18	0.44	0.56	69.00	35.00	69	Risky	gain	0.05	0.10
0.43	0.56	75.00	77	0.03	0.97	51.00	74.00	51	Risky	gain	0.19	0.46
0.45	0.55	55.00	99	0.68	0.32	71.00	59.00	71	Risky	gain	0.71	0.65
0.45	0.55	64.00	15	0.68	0.32	65.00	56.00	65	Risky	gain	0.01	0.05
0.46	0.54	6.00	87	0.67	0.33	23.00	78.00	23	Risky	gain	0.29	0.35
0.47	0.53	45.00	87	0.04	0.96	21.00	81.00	21	Risky	gain	0.39	0.26
0.72	0.28	66.00	70	0.16	0.84	59.00	63.00	59	Risky	gain	0.91	0.64
0.73	0.27	35.00	79	0.74	0.26	55.00	1.00	55	Risky	gain	0.16	0.31
0.77	0.23	42.00	99	0.22	0.78	80.00	86.00	80	Risky	gain	0.00	0.07
0.91	0.09	96.00	40	0.27	0.73	7.00	77.00	7	Risky	gain	0.00	0.05
0.02	0.98	100.00	59	1.00	0.00	93.00	0.00	93	Simple Safe	gain	0.00	0.03
0.03	0.97	55.00	92	1.00	0.00	71.00	0.00	71	Simple Safe	gain	0.78	0.65
0.03	0.97	90.00	68	1.00	0.00	89.00	0.00	89	Simple Safe	gain	0.01	0.05
0.16	0.84	21.00	95	1.00	0.00	53.00	0.00	53	Simple Safe	gain	0.68	0.51
0.17	0.83	15.00	74	1.00	0.00	39.00	0.00	39	Simple Safe	gain	0.74	0.60
0.17	0.83	94.00	35	1.00	0.00	80.00	0.00	80	Simple Safe	gain	0.01	0.04
0.18	0.82	92.00	30	1.00	0.00	47.00	0.00	47	Simple Safe	gain	0.29	0.23
0.19	0.81	27.00	97	1.00	0.00	49.00	0.00	49	Simple Safe	gain	0.78	0.50
0.39	0.61	75.00	16	1.00	0.00	48.00	0.00	48	Simple Safe	gain	0.07	0.07
0.43	0.56	73.00	75	1.00	0.00	71.00	0.00	71	Simple Safe	gain	0.76	0.47
0.45	0.55	51.00	95	1.00	0.00	63.00	0.00	63	Simple Safe	gain	0.79	0.42
0.45	0.55	62.00	13	1.00	0.00	60.00	0.00	60	Simple Safe	gain	0.01	0.03
0.46	0.54	8.00	89	1.00	0.00	43.00	0.00	43	Simple Safe	gain	0.25	0.19
0.47	0.53	41.00	83	1.00	0.00	75.00	0.00	75	Simple Safe	gain	0.03	0.09
0.72	0.28	68.00	72	1.00	0.00	64.00	0.00	64	Simple Safe	gain	0.82	0.46
0.73	0.27	37.00	81	1.00	0.00	43.00	0.00	43	Simple Safe	gain	0.68	0.39
0.77	0.23	38.00	95	1.00	0.00	81.00	0.00	81	Simple Safe	gain	0.00	0.03
0.91	0.09	98.00	42	1.00	0.00	60.00	0.00	60	Simple Safe	gain	0.88	0.57
0.01	0.99	80.00	0	1.00	0.00	1.00	0.00	1	Simple Safe Zero	gain	0.53	0.36
0.01	0.99	100.00	0	1.00	0.00	0.80	0.00	0.8	Simple Safe Zero	gain	0.69	0.38
0.05	0.95	16.00	0	1.00	0.00	1.00	0.00	1	Simple Safe Zero	gain	0.50	0.39
0.05	0.95	20.00	0	1.00	0.00	0.80	0.00	0.8	Simple Safe Zero	gain	0.74	0.49
0.10	0.90	8.00	0	1.00	0.00	1.00	0.00	1	Simple Safe Zero	gain	0.51	0.35
0.10	0.90	10.00	0	1.00	0.00	0.80	0.00	0.8	Simple Safe Zero	gain	0.64	0.49
0.20	0.80	50.00	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.10	0.20
0.20	0.80	62.50	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.40	0.30
0.40	0.60	25.00	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.07	0.10
0.40	0.60	31.25	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.42	0.33
0.60	0.40	16.67	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.04	0.06
0.60	0.40	20.83	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.34	0.33
0.80	0.20	12.50	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.00	0.05
0.80	0.20	15.62	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.38	0.41
0.90	0.10	11.11	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.00	0.04
0.90	0.10	13.89	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.31	0.38
0.95	0.05	10.53	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.00	0.05
0.95	0.05	13.16	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.42	0.38
0.99	0.01	10.10	0	1.00	0.00	12.50	0.00	12.5	Simple Safe Zero	gain	0.04	0.03
0.99	0.01	12.63	0	1.00	0.00	10.00	0.00	10	Simple Safe Zero	gain	0.62	0.72

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B | Supplemental Materials to Chapter 3

B.1 Self-report Items

After completing the cognitive tasks, participants were asked to indicate their introspective risk preference on the one-item general risk question (cf. Dohmen et al., 2011), which reads as follows:

> *How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: "not at all willing to take risks" and the value 10 means: "very willing to take risks."*

They were also asked for a self-report regarding their impulsivity:

> *Do you generally think things over for a long time before acting – in other words, are you not impulsive at all? Or do you generally act without thinking things over a long time – in other words, are you very impulsive? Please tick a box on the scale, where the value 0 means "not at all impulsive" and the value 10 means "very impulsive". You can use the values in between to make your estimate.*

Moreover participants were asked for a self-report regarding their patience:

> *Are you generally an impatient person, or someone who always shows great patience? Please tick a box on the scale, where the value 0 means "very impatient" and the value 10 means "very patient". You can use the values in between to make your estimate.*

These three items are standard questions also used in the German Socio-Economic Panel (SOEP, cf. Richter et al., 2013).

B.2 Additional Analyses of Loss Aversion Task Choice Data

B.2.1 Choice Behavior on Non-distractor Trials with Advantageous Safe Options

Here we present results for the Bayesian GLMER models on choice behavior in the non-distractor loss aversion trials, where the safe option had a higher EV. Note that these trials are not diagnostic regarding loss aversion, since both loss averse participants and participants who simply maximize EVs are expected to choose the safe option. The tendency to choose the safe option in these trials (which can indicate both loss aversion and maximization) is displayed in Figure B.1.

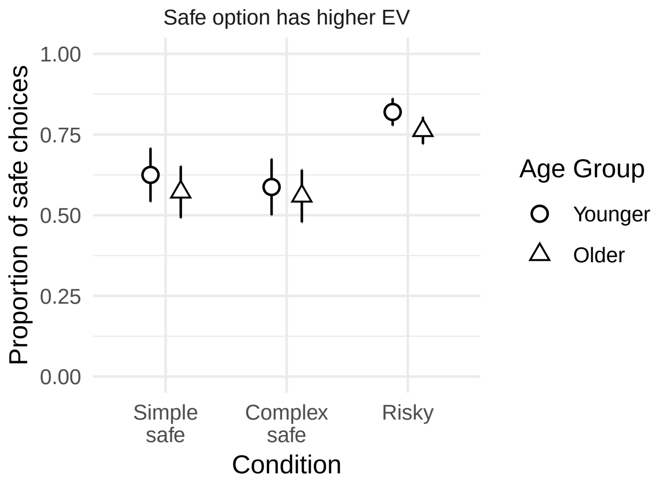

Figure B.1: Choice proportions in the loss aversion task, in non-distractor trials where the safe option has a higher EV than the safe option, conditional on the complexity manipulation. Behavior in these trials is not diagnostic regarding loss aversion. Error bars indicate 95 % confidence intervals.

Table B.1: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Loss Aversion Task, in Non-distractor Trials where the Safe Option had the higher EV

Outcome: Safe choice (when risky option has lower EV)		
Predictor	Main effect model	Interaction model
(Intercept)	**1.81** **[1, 2.66]**	**1.85** **[1.04, 2.7]**
Age group (older)	-0.4 [-0.92, 0.1]	-0.42 [-1.04, 0.17]
Condition (complex safe)	-0.13 [-0.39, 0.14]	-0.23 [-0.62, 0.16]
Condition (risky)	**1.29** **[1, 1.57]**	**1.4** **[0.99, 1.83]**
Self-report (risk)	**-0.21** **[-0.34, -0.07]**	**-0.21** **[-0.35, -0.08]**
Age group (older) × Condition (complex safe)		0.18 [-0.32, 0.73]
Age group (older) × Condition (risky)		-0.21 [-0.77, 0.35]

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We calculated Bayesian logistic GLMERs on the choice of the safe option as the outcome variable, including fixed predictors for age group, the complexity condition, as well as each participant's self-reported risk preference, and a random intercept for each participant (main effect model). We also calculated an analogue model including the interaction between the complexity condition and age group (interaction model). Results for trials where the safe option had a higher EV—which are not diagnostic regarding loss aversion—are displayed in Table B.1.

There was no credible main effect of age group and condition (complex safe) on the tendency to choose the safe option in these trials. There was a positive main effect of condition (risky), indicating that participants chose the safe (i.e., low risk) option more in choices between two risky options than in choices between a safe and a risky option. There were no credible interactions between age group and condition, indicating that younger and older adults were similarly insensitive to the complexity manipulation.

B.2.2 Choice Behavior on Distractor Trials

We analysed behavior on the distractor trials of the loss aversion task, where the safe option's EV was unequal zero (either -3 or +3). These trials do not correspond to commonly used choice lists for measuring loss aversion.

Advantageous and disadvantageous safe option choices

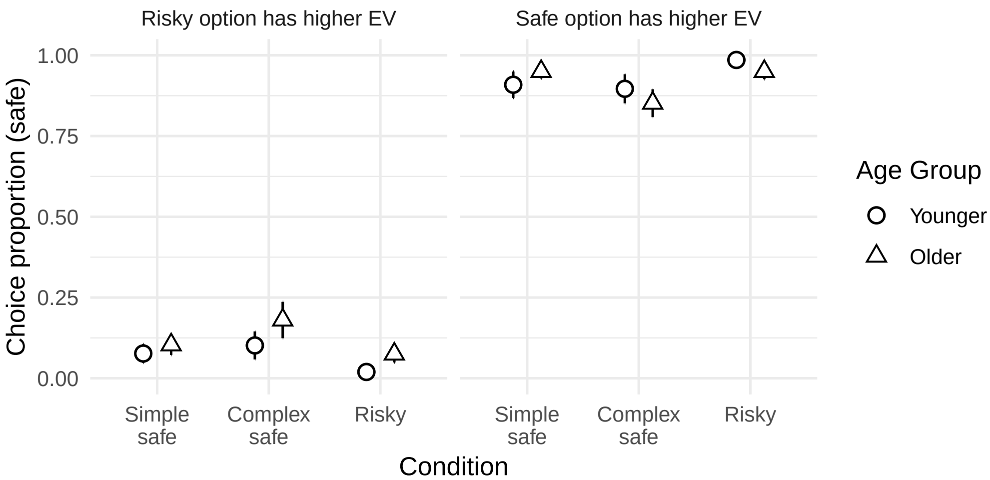

Figure B.2: Choice proportions of the safe option in the loss aversion task, in distractor trials where the safe options' EVs were not zero, conditional on the complexity manipulation. Left panel: Behavior on distractor trials where the risky option had a higher EV. Right panel: Behavior on distractor trials where the safe option had a higher EV. Error bars indicate 95 % confidence intervals.

The proportion of safe option choices in the distractor trials is shown in Figure B.2, separate for trials where the safe option was disadvantageous (left panel) and where the safe option was advantageous (right panel). We calculated Bayesian GLMERs to investigate whether the tendency to choose the safe option was affected by increasing the complexity of the safe option. The models used the choice of the safe (or low risk) option as the outcome variable, and included fixed predictors for age group, condition, and participants' self-reported risk preferences, as well as a random intercept for each participant (main effect model). We calculated an analogue model also including the interaction between age group and condition (interaction model). Both models were calculated separately for distractor trials where the safe option was disadvantageous, and where the safe option was advantageous. Results are displayed in Table B.2.

Table B.2: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Safe Option Choices on the Loss Aversion Task, in Distractor Trials where the Risky Option had the Higher EV (Upper Table), and where the Safe Option had the Higher EV (Lower Table)

Outcome: Safe choice (when risky option has higher EV)		
Predictor	Main effect model	Interaction model
(Intercept)	**-3.84** **[-4.8, -2.95]**	**-3.67** **[-4.64, -2.76]**
Age group (older)	**0.83** **[0.27, 1.39]**	0.47 [-0.21, 1.13]
Condition (complex safe)	**0.61** **[0.32, 0.9]**	0.38 [-0.06, 0.84]
Condition (risky)	**-0.79** **[-1.16, -0.43]**	**-1.52** **[-2.24, -0.86]**
Self-report (risk)	0.08 [-0.07, 0.23]	0.08 [-0.07, 0.23]
Age group (older) × Condition (complex safe)		0.41 [-0.17, 0.98]
Age group (older) × Condition (risky)		**1.09** **[0.29, 1.94]**

Outcome: Safe choice (when risky option has lower EV)		
Predictor	Main effect model	Interaction model
(Intercept)	**4.75** **[3.68, 5.9]**	**4.38** **[3.25, 5.55]**
Age group (older)	-0.5 [-1.15, 0.17]	0.44 [-0.37, 1.22]
Condition (complex safe)	**-0.8** **[-1.11, -0.47]**	-0.22 [-0.68, 0.22]
Condition (risky)	**0.96** **[0.52, 1.4]**	**2.19** **[1.49, 3.06]**
Self-report (risk)	**-0.19** **[-0.37, -0.01]**	**-0.19** **[-0.38, -0.01]**
Age group (older) × Condition (complex safe)		**-1.17** **[-1.82, -0.51]**
Age group (older) × Condition (risky)		**-2.16** **[-3.19, -1.26]**

In trials where the risky option had a higher EV, that is, where safe choices were disadvantageous, there was a positive main effect of age, indicating that older adults were overall more likely to make disadvantageous safe (or low risk) choices. There was also a positive main effect of condition (complex safe) indicating that increasing the complexity of safe options increased disadvantageous safe choices. Note that this finding speaks against complexity aversion. Increasing the complexity of disadvantageous safe options did not make them even less attractive (as expected under complexity aversion), but less *un*-attractive. Rather, the finding suggests that participants had less insight into the value of safe options when they were presented in a more complex format, and hence made more errors. There was a negative main effect of condition (risky), indicating that participants made overall less disadvantageous low risk choices when both options were risky, compared to when one option was safe. A credible interaction between condition (risky) and age group suggests that this effect was more pronounced in younger adults.

In trials where the risky option had a lower EV, that is, where safe choices were advantageous, increasing the complexity of safe option decreased participants' tendency to choose these options. This finding, too, is consistent with the interpretation that participants had less insight into the value of safe options when they were presented in a more complex format, and hence made more errors. There was also a credible interaction between age group and condition (complex safe): In older adults, the tendency to choose advantageous safe options decreased more strongly than in younger adults, when these options were presented in a more complex format. That is, older adults showed a stronger increase in disadvantageous risk taking when safe options' complexity was increased.

Overall, these findings suggest that the complexity manipulation had effects on choice behavior in trials where the safe option's EV was unequal zero. These effects indicate that increasing safe options' complexity was detrimental for decision quality, and this effect was—to some extent—more pronounced in older adults. In particular, older adults were especially prone to engage in disadvantageous risk taking when safe options' complexity increased. This replicates findings by Mamerow et al. (2016), who also report that older participants are particularly prone to engage in disadvantageous risk taking, and link this to the computational demands of the employed risky choice task.

However, note that overall, participants chose safe options in a majority of trials when they were advantageous, and rejected them in a majority of trials when they were disadvantageous. This indicates overall very high decision quality.

Analyses of decision quality

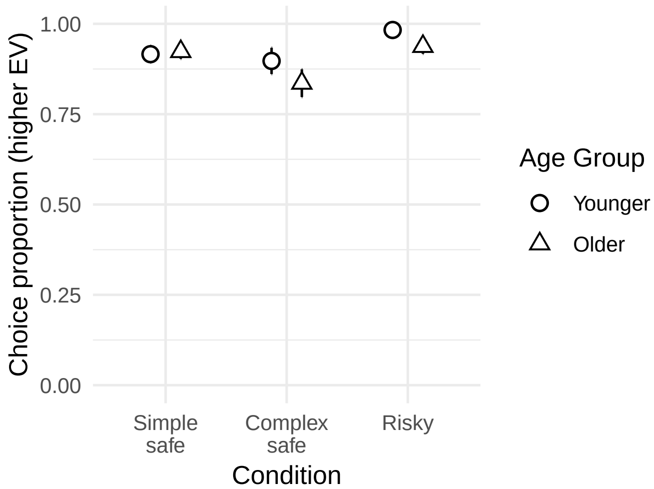

Figure B.3: Choice proportions of the option with the higher EV in distractor trials of the loss aversion task, where the safe option had an EV unequal to zero, conditional on the complexity manipulation. Error bars indicate 95 % confidence intervals.

We also directly analysed decision quality (the tendency to choose the option with the higher EV) across all distractor trials, without separating between trials where the safe or the risky option had the higher EV. Decision quality is implicit in the tendency to choose (dis-)advantageous safe options, illustrated in Figure B.2. A more direct illustration of the tendency to choose the option with the higher EV is provided in Figure B.3.

We calculated Bayesian GLMERs with the choice of the option with the higher EV as the outcome variable, including fixed predictors for age group, condition, participants self-reported risk preference, as well as a random intercept for each participant (main effect model). We also calulated an analogue model including the interaction between age group and condition (interaction model). Results are displayed in Table B.3. Further supporting our previous results, increasing safe options' complexity had a credible negative main effect on decision quality. There was also a credible interaction between safe options' complexity and age group, indicating that the decrease in decision quality due to higher option complexity was more pronounced in older adults. Hence, we

Table B.3: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Loss Aversion Task, in Distractor Trials

Outcome: Higher EV choice (distractor trials) Predictor	Main effect model	Interaction model
(Intercept)	**3.86** **[3.15, 4.63]**	**3.57** **[2.86, 4.36]**
Age group (older)	**-0.59** **[-1.05, -0.14]**	-0.02 [-0.55, 0.52]
Condition (complex safe)	**-0.64** **[-0.84, -0.43]**	-0.26 [-0.56, 0.05]
Condition (risky)	**0.81** **[0.54, 1.09]**	**1.75** **[1.29, 2.3]**
Self-report (risk)	-0.12 [-0.24, 0]	-0.12 [-0.24, 0]
Age group (older) × Condition (complex safe)		**-0.7** **[-1.12, -0.3]**
Age group (older) × Condition (risky)		**-1.51** **[-2.13, -0.9]**

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obtain evidence that older adults showed a stronger response to option complexity, similar to our previous findings. However, in the task employed here, this greater response to option complexity affected decision quality, not as hypothesized, the tendency to choose safe options indicative of loss aversion.

B.3 Additional Analyses of Intertemporal Choice Data

We used data from the attention check trials in the intertemporal choice task to assess how increasing immediate options' complexity affected violations of dominance. In these trials, the option that could be obtained sooner also offered the larger amount. We calculated a Bayesian GLMER with the choice of the larger sooner option as the outcome variable, and age group, condition as well as the self-reported patience and impulsivity as fixed predictors, and a random intercept for each participant (main effect model). We also calculated an analogue model including the interaction of age group an condition (interaction model). As Table B.4 shows, increasing immediate options' complexity had a credible negative main effect on the tendency to choose the dominant immediate option. This affected both younger and older adults alike, as indicated by the interaction between age group and condition (complex immediate) not being significant. This result provides further evidence that option complexity negatively affected decision quality (similar to the findings on the distractor trials of the loss aversion task).

Table B.4: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Attention Check Trials in the Intertemporal Choice Task

Outcome: Larger sooner choice Predictor	Main effect model	Interaction model
(Intercept)	**5.36** **[4.16, 6.7]**	**5.16** **[3.85, 6.57]**
Age group (older)	-0.49 [-1.02, 0.02]	-0.05 [-1.25, 1.17]
Condition (complex immediate)	**-2.85** **[-3.53, -2.25]**	**-2.58** **[-3.51, -1.78]**
Condition (delayed)	-0.3 [-1.11, 0.52]	-0.3 [-1.39, 0.79]
Self-report (patience)	0.03 [-0.08, 0.15]	0.03 [-0.08, 0.15]
Self-report (impulsivity)	-0.05 [-0.18, 0.09]	-0.05 [-0.19, 0.09]
Age group (older) × Condition (complex immediate)		-0.54 [-1.75, 0.67]
Age group (older) × Condition (delayed)		-0.02 [-1.52, 1.47]

B.4 Additional Analyses of Framing Task Choice Data

Using the choice data from the framing task, we also tested whether the complexity manipulation affected choice behavior within each age group and frame. We tested this by calculating Bayesian logistic GLMERs with the choice of the manipulated option the framing task as the outcome variable, and condition as a fixed predictor, as well as a random intercept for each participant. Such a model was calculated separately for the positively and negatively framed trials. As Table B.5 shows, the manipulation of option complexity had no credible main effect on choice behavior in any age group or frame.

Table B.5: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Responses on the Framing Task, by Age Group, within each Frame

Outcome: Safe choice	Younger		Older	
Predictor	Positive Frame	Negative Frame	Positive Frame	Negative Frame
(Intercept)	**1.59** **[1.14, 2.08]**	**-0.7** **[-1.13, -0.27]**	**1.89** **[1.48, 2.36]**	**-0.7** **[-1.06, -0.35]**
Condition (complex safe)	-0.18 [-0.55, 0.2]	-0.04 [-0.39, 0.29]	0.28 [-0.13, 0.68]	-0.2 [-0.52, 0.14]
Condition (risky)	-0.11 [-0.47, 0.27]	0.03 [-0.3, 0.37]	-0.04 [-0.42, 0.35]	0.04 [-0.27, 0.35]

B.5 Analyses of Response Time Data

Besides analysing choice proportions in each paradigm, we also conducted an exploratory analysis of response times (RTs). In our previous experiments on the effect of option complexity (Zilker et al., 2019; Zilker & Pachur, 2019, see chapter 2 and 4), increasing the complexity of one or both options in the choice set was very consistently linked to higher RTs. We tested whether the manipulation of option complexity also entailed longer RTs in the tasks employed here.

B.5.1 Response Times in the Loss Aversion Task

Response times in the non-distractor trials of the loss aversion task are depicted in Figure B.4. We calculated Bayesian GLMERs on RT as the outcome variable, including fixed predictors for age group, condition and participants' self-reported risk preference, as well as a random intercept for each participant (main effect model). We also calculated analogue models including the interaction between age group and condition (interaction model). These models were calculated separately for the trials where the risky option had a higher EV and for trials where the safe option had a higher EV. The results are displayed in Table B.6. Older adults generally responded slower. Increasing the complexity of safe options had a credible positive main effect on RTs. In trials where the risky option had a lower EV this effect interacted with age group. That is, participants took more time to respond to trials with more complex safe options, and this effect was more pronounced in older adults.

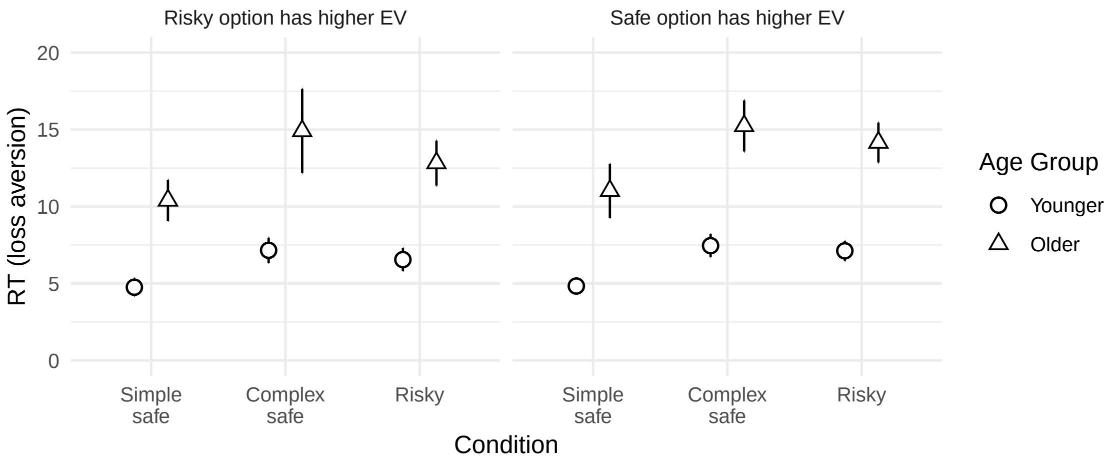

Figure B.4: Response times in the non-distractor trials in the loss aversion task. Error bars indicate 95 % confidence intervals.

B.5.2 Response Times in the Framing Task

Using RT data from the framing task, we tested whether increasing safe options' complexity also increased RTs, and whether this depended on frame. RTs in each condition, both age groups and frames are displayed in Figure B.5. We calculated Bayesian GLMERs with RT as the outcome variable, including frame and condition as fixed predictors, and a random intercept for each participant (main effect model). We also calculated analogue models including the interaction between frame and condition (interaction model). These models were calculated separately for each age group. Results are displayed in Table B.7.

Table B.6: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Response Times on the Loss Aversion Task

Outcome: RT (when risky option has higher EV)		
Predictor	Main effect model	Interaction model
(Intercept)	**4.34** **[1.91, 6.89]**	**4.82** **[2.02, 7.32]**
Age group (older)	**6.43** **[4.83, 8.13]**	**5.52** **[3.57, 7.62]**
Condition (complex safe)	**3.42** **[2.26, 4.59]**	**2.38** **[0.75, 4.06]**
Condition (risky)	**2.11** **[0.83, 3.37]**	1.78 [-0.03, 3.61]
Self-report (risk)	0 [-0.44, 0.41]	-0.01 [-0.42, 0.44]
Age group (older) × Condition (complex safe)		2.14 [-0.22, 4.43]
Age group (older) × Condition (risky)		0.6 [-1.94, 3.18]
Outcome: RT (when risky option has lower EV)		
Predictor	Main effect model	Interaction model
(Intercept)	**4.44** **[2.3, 6.52]**	**4.87** **[2.6, 7.04]**
Age group (older)	**6.89** **[5.41, 8.34]**	**6.04** **[4.42, 7.75]**
Condition (complex safe)	**3.44** **[2.66, 4.25]**	**2.61** **[1.54, 3.79]**
Condition (risky)	**2.66** **[1.92, 3.42]**	**2.27** **[1.22, 3.37]**
Self-report (risk)	0 [-0.36, 0.37]	0 [-0.37, 0.37]
Age group (older) × Condition (complex safe)		**1.68** **[0.12, 3.26]**
Age group (older) × Condition (risky)		0.81 [-0.69, 2.32]

Older adults' RTs were generally longer in the negative than in the positive frame, indicated by the main effects of frame (negative). This effect was not credible in younger adults. Moreover, in both age groups, RTs were overall longer when the second option was a complex safe option or a second risky option, than when it was a simple safe option. Finally, there was a credible interaction between frame and condition (complex safe) in both age groups. That is, increasing the complexity of safe options entailed a stronger increase in RTs in the domain of losses, than in the domain of gains, in both age groups.

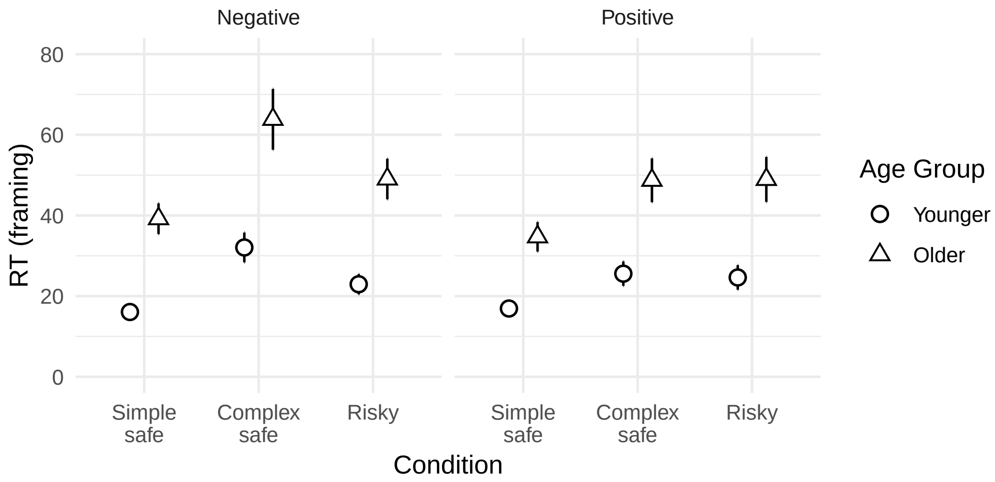

Figure B.5: Response times in the framing task. Error bars indicate 95 % confidence intervals.

Table B.7: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Response Times on the Framing Task, by Age Group, within each Frame

Outcome: RT	Younger		Older	
Predictor	Main effect model	Interaction model	Main effect model	Interaction model
(Intercept)	**15.83** **[13.64, 18.14]**	**16.94** **[14.34, 19.49]**	**33.66** **[28.84, 38.24]**	**34.37** **[29.01, 40.02]**
Frame (negative)	1.31 [-0.02, 2.65]	-0.86 [-3.13, 1.38]	**6.55** **[4.03, 9.08]**	**4.52** **[0.13, 9.02]**
Condition (complex safe)	**12.32** **[10.75, 13.91]**	**8.65** **[6.41, 10.89]**	**19.32** **[16.16, 22.41]**	**14.1** **[9.81, 18.5]**
Condition (risky)	**7.31** **[5.71, 8.88]**	**7.7** **[5.49, 9.99]**	**12.06** **[8.89, 15.19]**	**14.32** **[9.94, 18.69]**
Frame × Condition (complex safe)		**7.35** **[4.28, 10.56]**		**10.51** **[4.29, 16.56]**
Frame × Condition (risky)		-0.8 [-4.05, 2.36]		-4.37 [-10.52, 1.82]

B.5.3 Response Times in the Intertemporal Choice Task

Response times in the intertemporal choice task are depicted in Figure B.6. We analysed response times in the intertemporal choice task, in the non-dominated trials. We calculated Bayesian GLMERs on RT as the outcome variable, including fixed predictors for age group, condition and participants' self-reported patience and impulsivity, as well as a random intercept for each participant (main effect model). We also calculated analogue models including the interaction between age group and condition (interaction model). The results are displayed in Table B.8. Increasing the complexity of immediate options had a credible positive main effect on RTs, and this effect was more pronounced in older adults. That is, participants took more time to respond to trials with more complex options, and this effect was more pronounced in older adults.

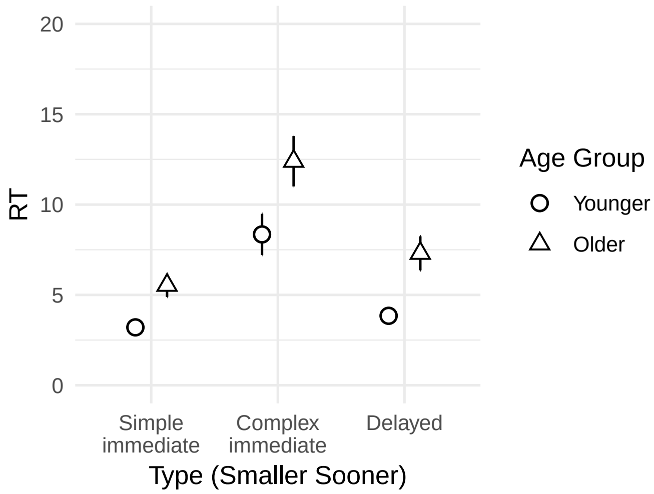

Figure B.6: Response times in the intertemporal choice task. Error bars indicate 95 % confidence intervals.

Table B.8: Coefficients and 95 % Posterior Intervals for the Bayesian Logistic GLMERs for Response Times on the Non-dominated Trials of the Intertemporal Choice Task

Outcome: RT Predictor	Main effect model	Interaction model
(Intercept)	2 [-0.15, 4.28]	**2.61** **[0.55, 4.9]**
Age group (older)	**3.08** **[1.96, 4.19]**	**2.07** **[1.04, 3.23]**
Condition (complex immediate)	**6.03** **[5.75, 6.3]**	**5.14** **[4.75, 5.53]**
Condition (delayed)	**1.16** **[0.87, 1.44]**	**0.64** **[0.23, 1.04]**
Self-report (patience)	0.09 [-0.15, 0.32]	0.09 [-0.14, 0.29]
Self-report (impulsivity)	0.05 [-0.23, 0.31]	0.02 [-0.25, 0.26]
Age group (older) × Condition (complex immediate)		**1.77** **[1.21, 2.35]**
Age group (older) × Condition (delayed)		**1.06** **[0.48, 1.61]**

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C | Supplemental Materials to Chapter 4

C.1 Behavioral Analyses: Figure for Behavior in Choices Between Two Risky Options

In the main text we focused on reporting the results of the behavioral analyses for choices between safe and risky options. The behavioral patterns for choices between two risky options are displayed in Figure C.1.

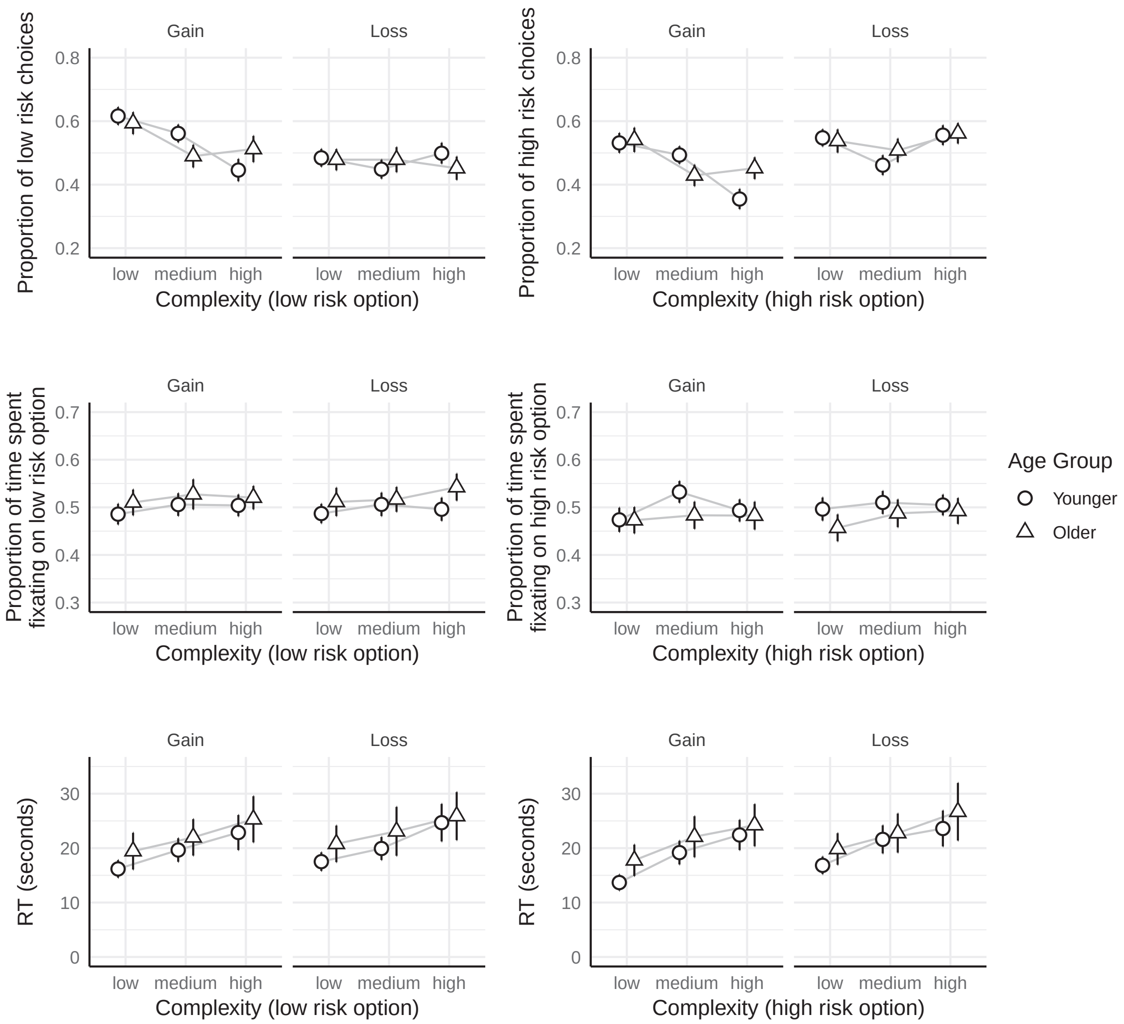

Figure C.1: Effects of option complexity on risky choice, gaze behavior, response times in choices between two risky options. Error bars indicate 95% CI.

C.2 Behavioral Analyses: Tables for GLMERs on Risky Choice Behavior

We calculated Bayesian GLMERs on choices of the high risk option as the outcome variable. The models included fixed effects for option complexity (separate for both options), age group, the interaction between option complexity and age group, the absolute difference in EV between the options, a dummy variable indicating whether the more risky option had a higher EV, and a random intercept for each participant. All models are estimated separately for each domain (gains and losses) and type of choice problem (safe vs. risky and risky vs. risky). We also calculated analogue models for the main effects of complexity on each outcome within each age group (including all predictors listed above, except for age group and its interaction with option complexity).

Table C.1 displays the GLMER results for the analysis of choices of the high risk option as the outcome variable, in each domain and type of choice problem, testing for the interaction between option complexity and age. Table C.2 displays the respective results for the model testing for the main effect of complexity within each age group. Tables include β coefficients and the respective 95% posterior intervals for all fixed effects in these models.

Table C.1: GLMER Results (β Coefficients and 95% Posterior Intervals) for Choices of the High Risk Option as the Outcome Variable

	Risky vs. Safe		Risky vs. Risky	
Predictor	Gain	Loss	Gain	Loss
Intercept	-0.05 [-0.7, 0.64]	**-0.63** **[-1.05, -0.21]**	**-1.05** **[-1.32, -0.78]**	**-0.63** **[-0.86, -0.4]**
Age Group (Older)	-0.38 [-0.96, 0.18]	-0.03 [-0.57, 0.49]	0.11 [-0.15, 0.37]	-0.03 [-0.3, 0.22]
Complexity high risk (medium)	**-0.5** **[-0.8, -0.2]**	0.1 [-0.18, 0.4]	-0.14 [-0.36, 0.06]	-0.19 [-0.39, 0.02]
Complexity high risk (high)	**-0.56** **[-0.87, -0.25]**	-0.18 [-0.47, 0.12]	**-0.62** **[-0.84, -0.41]**	0.19 [-0.02, 0.39]
Complexity low risk (medium)	-0.26 [-0.62, 0.11]	-0.29 [-0.6, 0]	**0.29** **[0.1, 0.48]**	0.03 [-0.17, 0.22]
Complexity low risk (high)	0.03 [-0.29, 0.34]	0.17 [-0.13, 0.47]	**0.66** **[0.45, 0.87]**	-0.13 [-0.33, 0.06]
EV difference	**-0.1** **[-0.13, -0.06]**	**0.05** **[0.03, 0.08]**	0.01 [-0.01, 0.02]	0.01 [-0.01, 0.02]
Higher EV equals higher Risk (True)	**1.25** **[0.98, 1.53]**	**1.2** **[1.01, 1.4]**	**1.49** **[1.37, 1.61]**	**1.4** **[1.28, 1.52]**
Age Group (Older) × Complexity high risk (medium)	0.14 [-0.31, 0.58]	-0.04 [-0.47, 0.38]	**-0.4** **[-0.71, -0.11]**	0.23 [-0.04, 0.51]
Age Group (Older) × Complexity high risk (high)	-0.12 [-0.57, 0.34]	0.01 [-0.41, 0.43]	**0.4** **[0.1, 0.7]**	0.02 [-0.27, 0.31]
Age Group (Older) × Complexity low risk (medium)	-0.02 [-0.52, 0.45]	-0.02 [-0.45, 0.41]	0.2 [-0.09, 0.47]	-0.19 [-0.46, 0.09]
Age Group (Older) × Complexity low risk (high)	**0.64** **[0.16, 1.1]**	0.13 [-0.3, 0.55]	**-0.39** **[-0.67, -0.1]**	0.16 [-0.11, 0.43]

Table C.2: GLMER Results (β Coefficients and 95% Posterior Intervals) for Choices of the High Risk Option as the Outcome Variable, within each Age Group, by Type of Choice Problem

	Risky vs. Safe		Risky vs. Risky	
Predictor	Younger	Older	Younger	Older
Gains				
Intercept	0.085 [-0.8, 0.971]	-0.391 [-1.292, 0.52]	**-1.34** **[-1.666, -1.021]**	**-0.681** **[-1.001, -0.363]**
Complexity high risk (medium)	**-0.568** **[-0.898, -0.245]**	**-0.326** **[-0.655, -0.002]**	-0.117 [-0.333, 0.108]	**-0.554** **[-0.771, -0.333]**
Complexity high risk (high)	**-0.611** **[-0.941, -0.291]**	**-0.64** **[-0.978, -0.303]**	**-0.61** **[-0.818, -0.395]**	**-0.261** **[-0.464, -0.051]**
Complexity low risk (medium)	-0.415 [-0.831, 0.006]	-0.174 [-0.601, 0.237]	**0.31** **[0.111, 0.514]**	**0.459** **[0.27, 0.642]**
Complexity low risk (high)	-0.009 [-0.356, 0.344]	**0.654** **[0.31, 0.98]**	**0.658** **[0.451, 0.871]**	**0.296** **[0.102, 0.496]**
EV difference	**-0.131** **[-0.182, -0.081]**	**-0.07** **[-0.118, -0.023]**	0.014 [-0.004, 0.034]	0.001 [-0.017, 0.019]
Higher EV equals higher Risk (True)	**1.789** **[1.394, 2.201]**	**0.628** **[0.249, 1.023]**	**1.847** **[1.667, 2.018]**	**1.149** **[0.982, 1.318]**
Losses				
Intercept	**-0.981** **[-1.426, -0.52]**	-0.301 [-0.786, 0.187]	**-0.88** **[-1.157, -0.601]**	**-0.426** **[-0.71, -0.156]**
Complexity high risk (medium)	0.111 [-0.192, 0.41]	0.063 [-0.267, 0.382]	-0.144 [-0.359, 0.072]	-0.009 [-0.219, 0.208]
Complexity high risk (high)	-0.194 [-0.525, 0.133]	-0.146 [-0.474, 0.185]	**0.225** **[0.019, 0.441]**	0.17 [-0.035, 0.377]
Complexity low risk (medium)	**-0.328** **[-0.638, -0.014]**	-0.305 [-0.623, 0.002]	-0.015 [-0.227, 0.194]	-0.11 [-0.31, 0.085]
Complexity low risk (high)	0.183 [-0.151, 0.514]	0.276 [-0.045, 0.606]	-0.184 [-0.394, 0.026]	0.064 [-0.14, 0.261]
EV difference	**0.061** **[0.026, 0.095]**	**0.048** **[0.013, 0.084]**	0.015 [-0.006, 0.035]	0 [-0.019, 0.021]
Higher EV equals higher Risk (True)	**1.815** **[1.527, 2.115]**	**0.538** **[0.259, 0.828]**	**1.752** **[1.589, 1.919]**	**1.045** **[0.892, 1.207]**

C.3 Behavioral Analyses: Tables for GLMERs on RTs

We calculated Bayesian GLMERs on RTs as the outcome variable. The models included fixed effects for option complexity (separate for both options), age group, the interaction between option complexity and age group, the absolute difference in EV between the options, a dummy variable indicating whether the more risky option had a higher EV, and a random intercept for each participant. All models were estimated separately for each domain (gains and losses) and type of choice problem (safe vs. risky and risky vs. risky). We also calculated analogue models for the main effects of complexity on each outcome within each age group (including all predictors listed above, except for age group and its interaction with option complexity).

Table C.3 displays the GLMER results for the analysis of response time as the outcome variable, in each domain and type of choice problem, testing for the interaction between option complexity and age. Table C.4 displays the respective results for the model testing for the main effect of complexity within each age group. Tables include β coefficients and the respective 95% posterior intervals for all fixed effects in these models.

Table C.3: GLMER Results (β Coefficients and 95% Posterior Intervals) for RT as the Outcome Variable

	Risky vs. Safe		Risky vs. Risky	
Predictor	Gain	Loss	Gain	Loss
Intercept	**8.51** **[5.47, 11.65]**	**10.28** **[7.55, 12.94]**	**13.03** **[9.97, 16.15]**	**15.23** **[11.96, 18.66]**
Age Group (Older)	3.04 [-0.2, 6.42]	2.7 [-0.57, 6.3]	**4.27** **[0.23, 8.13]**	4.01 [-0.7, 8.43]
Complexity high risk (medium)	**4.74** **[3.47, 5.98]**	**3.9** **[2.63, 5.26]**	**4.5** **[3.52, 5.48]**	**3.26** **[2.22, 4.32]**
Complexity high risk (high)	**8.15** **[6.93, 9.37]**	**7.64** **[6.31, 8.96]**	**7.87** **[6.9, 8.83]**	**6.17** **[5.15, 7.24]**
Complexity low risk (medium)	**3.03** **[1.63, 4.42]**	**3.68** **[2.39, 4.97]**	**3.6** **[2.7, 4.48]**	**3.15** **[2.14, 4.15]**
Complexity low risk (high)	**7.72** **[6.5, 8.95]**	**6.66** **[5.29, 7.96]**	**5.73** **[4.8, 6.62]**	**7.19** **[6.15, 8.18]**
EV difference	-0.09 [-0.21, 0.03]	-0.08 [-0.18, 0.03]	**-0.12** **[-0.18, -0.06]**	**-0.14** **[-0.21, -0.07]**
Higher EV equals higher Risk (True)	0.03 [-0.95, 1.05]	0.49 [-0.38, 1.37]	-0.05 [-0.6, 0.51]	0.11 [-0.49, 0.72]
Age Group (Older) × Complexity high risk (medium)	**-2.25** **[-3.98, -0.42]**	-1.71 [-3.67, 0.14]	**-1.46** **[-2.91, -0.09]**	-1.31 [-2.89, 0.13]
Age Group (Older) × Complexity high risk (high)	**-3.21** **[-5.05, -1.43]**	**-2.94** **[-4.77, -1.08]**	**-2.18** **[-3.56, -0.8]**	-0.84 [-2.34, 0.67]
Age Group (Older) × Complexity low risk (medium)	-1.03 [-2.83, 0.78]	**-2.55** **[-4.46, -0.65]**	-0.88 [-2.14, 0.36]	-0.49 [-1.91, 0.98]
Age Group (Older) × Complexity low risk (high)	**-1.89** **[-3.63, -0.18]**	**-2.1** **[-4.04, -0.29]**	-0.72 [-2.01, 0.58]	**-2.04** **[-3.44, -0.67]**

Table C.4: GLMER Results (β Coefficients and 95% Posterior Intervals) for RT as the Outcome Variable, within each Age Group, by Type of Choice Problem

Predictor	Risky vs. Safe Younger	Risky vs. Safe Older	Risky vs. Risky Younger	Risky vs. Risky Older
Gains				
Intercept	**10.17 [6.6, 13.95]**	**9.78 [6.17, 13.65]**	**13.08 [10.52, 15.52]**	**17.17 [13.79, 20.68]**
Complexity high risk (medium)	**4.62 [3.35, 5.93]**	**2.58 [1.34, 3.82]**	**4.42 [3.33, 5.44]**	**3.1 [2.17, 4.05]**
Complexity high risk (high)	**8.05 [6.67, 9.32]**	**5.06 [3.82, 6.29]**	**7.87 [6.84, 8.93]**	**5.69 [4.79, 6.58]**
Complexity low risk (medium)	**2.45 [0.89, 4.02]**	**2.59 [1.1, 4.04]**	**3.58 [2.63, 4.53]**	**2.72 [1.92, 3.55]**
Complexity low risk (high)	**7.52 [6.25, 8.84]**	**5.99 [4.76, 7.24]**	**5.68 [4.71, 6.65]**	**5.06 [4.21, 5.91]**
EV difference	**-0.2 [-0.37, -0.03]**	0.02 [-0.14, 0.18]	**-0.15 [-0.24, -0.06]**	**-0.09 [-0.17, -0.02]**
Higher EV equals higher Risk (True)	-0.52 [-1.98, 1.01]	0.64 [-0.73, 1.99]	0.1 [-0.75, 0.92]	-0.21 [-0.93, 0.52]
Losses				
Intercept	**9.74 [6.95, 12.53]**	**13.55 [10.77, 16.36]**	**15.5 [12.66, 18.36]**	**19.35 [15.51, 23.27]**
Complexity high risk (medium)	**3.91 [2.46, 5.33]**	**2.21 [1.01, 3.39]**	**3.2 [2.06, 4.36]**	**1.96 [0.96, 3]**
Complexity high risk (high)	**7.47 [5.93, 8.92]**	**4.9 [3.69, 6.21]**	**6.15 [5.03, 7.25]**	**5.35 [4.33, 6.34]**
Complexity low risk (medium)	**3.69 [2.23, 5.11]**	1.13 [-0.07, 2.34]	**3.14 [2.09, 4.22]**	**2.67 [1.69, 3.65]**
Complexity low risk (high)	**6.85 [5.33, 8.37]**	**4.23 [2.93, 5.56]**	**7.24 [6.16, 8.29]**	**5.11 [4.11, 6.09]**
EV difference	-0.01 [-0.17, 0.17]	**-0.15 [-0.3, -0.01]**	**-0.16 [-0.27, -0.05]**	**-0.12 [-0.21, -0.02]**
Higher EV equals higher Risk (True)	0.19 [-1.13, 1.51]	0.83 [-0.35, 1.98]	0.4 [-0.49, 1.29]	-0.18 [-0.99, 0.62]

C.4 Behavioral Analyses: Tables for GLMERs on Decision Quality

We calculated Bayesian GLMERs on choice of the option with the higher EV as the outcome variable as the outcome variable. The models included fixed effects for option complexity (separate for both options), age group, the interaction between option complexity and age group, the absolute difference in EV between the options, a dummy variable indicating whether the more risky option had a higher EV, and a random intercept for each participant. All models are estimated separately for each domain (gains and losses) and type of choice problem (safe vs. risky and risky vs. risky). We also calculated analogue models for the main effects of complexity on each outcome within each age group (including all predictors listed above, except for age group and its interaction with option complexity).

Table C.5 displays the GLMER results for the analysis of decision quality, that is, the tendency to choose the option with the higher EV, in each domain and type of choice problem, testing for the interaction between option complexity and age. Table C.6 displays the respective results for the model testing for the main effect of complexity within each age group. Tables include β coefficients and the respective 95% posterior intervals for all fixed effects in these models.

Table C.5: GLMER Results (β Coefficients and 95% Posterior Intervals) for Choices of the Option with the Higher EV as the Outcome Variable

	Risky vs. Safe		Risky vs. Risky	
Predictor	Gain	Loss	Gain	Loss
Intercept	**3.11** **[2.48, 3.71]**	**0.91** **[0.57, 1.26]**	**1.39** **[1.11, 1.69]**	**1.19** **[0.93, 1.45]**
Age Group (Older)	**-1.25** **[-1.69, -0.79]**	**-1.06** **[-1.47, -0.67]**	**-0.76** **[-1.08, -0.44]**	**-0.8** **[-1.08, -0.5]**
Complexity high risk (medium)	**-0.72** **[-1.04, -0.4]**	-0.29 [-0.59, 0.01]	**-0.7** **[-0.93, -0.46]**	**-0.54** **[-0.76, -0.32]**
Complexity high risk (high)	**-0.88** **[-1.19, -0.57]**	**-0.34** **[-0.64, -0.03]**	**-0.56** **[-0.8, -0.33]**	**-0.68** **[-0.9, -0.46]**
Complexity low risk (medium)	**-0.62** **[-0.99, -0.26]**	**-0.65** **[-0.96, -0.36]**	**-0.31** **[-0.52, -0.1]**	**-0.3** **[-0.51, -0.08]**
Complexity low risk (high)	**-0.49** **[-0.81, -0.16]**	**-0.41** **[-0.73, -0.1]**	-0.17 [-0.38, 0.05]	**-0.47** **[-0.68, -0.26]**
EV difference	-0.02 [-0.05, 0.01]	**0.04** **[0.01, 0.06]**	**0.04** **[0.03, 0.05]**	**0.03** **[0.02, 0.05]**
Higher EV equals higher Risk (True)	**-1.73** **[-1.98, -1.47]**	**0.48** **[0.3, 0.66]**	**-0.4** **[-0.52, -0.29]**	**0.19** **[0.07, 0.31]**
Age Group (Older) × Complexity high risk (medium)	0.35 [-0.09, 0.79]	0.13 [-0.28, 0.53]	**0.39** **[0.06, 0.7]**	**0.42** **[0.12, 0.71]**
Age Group (Older) × Complexity high risk (high)	**0.66** **[0.23, 1.1]**	0.15 [-0.25, 0.55]	0.28 [-0.04, 0.6]	**0.47** **[0.18, 0.77]**
Age Group (Older) × Complexity low risk (medium)	0.17 [-0.25, 0.6]	**0.59** **[0.18, 1]**	0.2 [-0.08, 0.48]	0.09 [-0.21, 0.38]
Age Group (Older) × Complexity low risk (high)	0.4 [-0.01, 0.85]	**0.43** **[0.04, 0.84]**	0.2 [-0.08, 0.51]	0.18 [-0.1, 0.46]

Table C.6: GLMER Results (β Coefficients and 95% Posterior Intervals) for Choices of the Option with the Higher EV as the Outcome Variable, within each Age Group, by Type of Choice Problem

	Risky vs. Safe		Risky vs. Risky	
Predictor	Younger	Older	Younger	Older
Gains				
Intercept	**3.35 [2.48, 4.26]**	**1.67 [0.95, 2.44]**	**1.36 [1.01, 1.71]**	**0.68 [0.36, 0.99]**
Complexity high risk (medium)	**-0.76 [-1.11, -0.42]**	**-0.34 [-0.64, -0.04]**	**-0.69 [-0.93, -0.44]**	**-0.33 [-0.56, -0.1]**
Complexity high risk (high)	**-0.93 [-1.27, -0.6]**	-0.19 [-0.5, 0.1]	**-0.58 [-0.81, -0.34]**	**-0.28 [-0.5, -0.07]**
Complexity low risk (medium)	**-0.67 [-1.1, -0.26]**	**-0.41 [-0.76, -0.04]**	**-0.32 [-0.53, -0.11]**	-0.11 [-0.3, 0.08]
Complexity low risk (high)	**-0.52 [-0.86, -0.19]**	-0.07 [-0.38, 0.23]	-0.16 [-0.37, 0.06]	0.03 [-0.17, 0.23]
EV difference	-0.02 [-0.07, 0.03]	-0.01 [-0.05, 0.03]	**0.05 [0.03, 0.07]**	**0.03 [0.02, 0.05]**
Higher EV equals higher Risk (True)	**-1.9 [-2.3, -1.52]**	**-1.57 [-1.94, -1.23]**	**-0.49 [-0.67, -0.31]**	**-0.32 [-0.49, -0.16]**
Losses				
Intercept	**0.8 [0.39, 1.19]**	-0.03 [-0.39, 0.35]	**1.12 [0.82, 1.46]**	**0.47 [0.19, 0.74]**
Complexity high risk (medium)	**-0.32 [-0.62, -0.02]**	-0.15 [-0.43, 0.12]	**-0.52 [-0.75, -0.3]**	-0.15 [-0.36, 0.06]
Complexity high risk (high)	**-0.4 [-0.72, -0.07]**	-0.15 [-0.43, 0.14]	**-0.68 [-0.92, -0.46]**	**-0.22 [-0.42, -0.02]**
Complexity low risk (medium)	**-0.68 [-0.99, -0.37]**	-0.06 [-0.34, 0.21]	**-0.31 [-0.54, -0.09]**	-0.19 [-0.4, 0]
Complexity low risk (high)	**-0.39 [-0.7, -0.07]**	-0.02 [-0.31, 0.27]	**-0.5 [-0.72, -0.29]**	**-0.26 [-0.46, -0.07]**
EV difference	**0.05 [0.02, 0.09]**	0.02 [-0.01, 0.06]	**0.04 [0.02, 0.07]**	0.02 [0, 0.04]
Higher EV equals higher Risk (True)	**0.54 [0.26, 0.82]**	**0.44 [0.18, 0.69]**	0.13 [-0.04, 0.3]	**0.24 [0.09, 0.4]**

C.5 Behavioral Analyses: Tables for GLMERs on Gaze Behavior

We calculated Bayesian GLMERs on proportion of time spent fixating on the high risk option as the outcome variable. The models included fixed effects for option complexity (separate for both options), age group, the interaction between option complexity and age group, the absolute difference in EV between the options, a dummy variable indicating whether the more risky option had a higher EV, and a random intercept for each participant. All models are estimated separately for each domain (gains and losses) and type of choice problem (safe vs. risky and risky vs. risky). We also calculated analogue models for the main effects of complexity on each outcome within each age group (including all predictors listed above, except for age group and its interaction with option complexity).

Table C.7 displays the GLMER results for the analysis of proportion of time fixating on the high risk option as the outcome variable, in each domain and type of choice problem, testing for the interaction between option complexity and age. Table C.8 displays the respective results for the model testing for the main effect of complexity within each age group. Tables include β coefficients and the respective 95% posterior intervals for all fixed effects in these models.

Table C.7: GLMER Results (β Coefficients and 95% Posterior Intervals) for the Proportion of Time Spent Fixating on the High Risk Option as the Outcome Variable

	Risky vs. Safe		Risky vs. Risky	
Predictor	Gain	Loss	Gain	Loss
Intercept	**0.44** **[0.36, 0.51]**	**0.42** **[0.38, 0.47]**	**0.47** **[0.44, 0.5]**	**0.52** **[0.49, 0.55]**
Age Group (Older)	0.04 [-0.02, 0.09]	0 [-0.05, 0.05]	0.01 [-0.02, 0.04]	-0.03 [-0.06, 0]
Complexity high risk (medium)	**-0.06** **[-0.1, -0.02]**	**-0.06** **[-0.09, -0.02]**	**0.06** **[0.04, 0.09]**	0.01 [-0.02, 0.03]
Complexity high risk (high)	**-0.08** **[-0.12, -0.04]**	**-0.07** **[-0.11, -0.04]**	0.02 [0, 0.05]	0.01 [-0.02, 0.03]
Complexity low risk (medium)	**0.08** **[0.04, 0.12]**	**0.1** **[0.06, 0.13]**	-0.02 [-0.05, 0]	-0.02 [-0.05, 0]
Complexity low risk (high)	**0.17** **[0.13, 0.2]**	**0.14** **[0.11, 0.18]**	-0.02 [-0.05, 0]	-0.01 [-0.04, 0.01]
EV difference	0 [-0.01, 0]	**0** **[0, 0]**	**0** **[0, 0]**	**0** **[0, 0]**
Higher EV equals higher Risk (True)	0 [-0.03, 0.03]	0.01 [-0.02, 0.03]	0.01 [-0.01, 0.02]	-0.01 [-0.02, 0.01]
Age Group (Older) × Complexity high risk (medium)	0 [-0.05, 0.05]	0.02 [-0.02, 0.08]	**-0.05** **[-0.09, -0.02]**	0.03 [0, 0.07]
Age Group (Older) × Complexity high risk (high)	0.01 [-0.04, 0.06]	0.01 [-0.04, 0.06]	-0.01 [-0.05, 0.03]	0.03 [0, 0.06]
Age Group (Older) × Complexity low risk (medium)	-0.01 [-0.07, 0.04]	-0.03 [-0.08, 0.02]	0.02 [-0.02, 0.05]	0.02 [-0.01, 0.05]
Age Group (Older) × Complexity low risk (high)	**-0.06** **[-0.11, -0.01]**	-0.01 [-0.07, 0.03]	0.01 [-0.03, 0.04]	-0.02 [-0.05, 0.01]

Table C.8: GLMER Results (β Coefficients and 95% Posterior Intervals) for the Proportion of Time Spent Fixating on the High Risk Option as the Outcome Variable, within each Age Group, by Type of Choice Problem

	Risky vs. Safe		Risky vs. Risky	
Predictor	Younger	Older	Younger	Older
Gains				
Intercept	**0.43** **[0.35, 0.52]**	**0.48** **[0.38, 0.57]**	**0.49** **[0.45, 0.53]**	**0.46** **[0.42, 0.5]**
Complexity high risk (medium)	**-0.06** **[-0.1, -0.03]**	**-0.06** **[-0.1, -0.02]**	**0.06** **[0.03, 0.09]**	0.02 [-0.01, 0.05]
Complexity high risk (high)	**-0.08** **[-0.12, -0.05]**	**-0.07** **[-0.11, -0.03]**	0.02 [-0.01, 0.05]	0.02 [-0.01, 0.04]
Complexity low risk (medium)	**0.07** **[0.03, 0.12]**	**0.06** **[0.01, 0.11]**	-0.02 [-0.05, 0]	-0.01 [-0.03, 0.02]
Complexity low risk (high)	**0.17** **[0.13, 0.2]**	**0.11** **[0.07, 0.15]**	-0.02 [-0.04, 0]	-0.02 [-0.04, 0.01]
EV difference	0 [-0.01, 0]	0 [-0.01, 0]	**0** **[0, 0]**	**0** **[0, 0]**
Higher EV equals higher Risk (True)	0.03 [-0.01, 0.06]	-0.03 [-0.07, 0.02]	0 [-0.02, 0.02]	0.02 [0, 0.04]
Losses				
Intercept	**0.43** **[0.38, 0.48]**	**0.42** **[0.36, 0.47]**	**0.52** **[0.48, 0.55]**	**0.5** **[0.47, 0.53]**
Complexity high risk (medium)	**-0.06** **[-0.09, -0.02]**	-0.03 [-0.07, 0.01]	0.01 [-0.01, 0.03]	**0.04** **[0.01, 0.06]**
Complexity high risk (high)	**-0.07** **[-0.11, -0.04]**	**-0.06** **[-0.1, -0.03]**	0.01 [-0.02, 0.03]	**0.03** **[0.01, 0.06]**
Complexity low risk (medium)	**0.1** **[0.06, 0.13]**	**0.07** **[0.03, 0.1]**	-0.03 [-0.05, 0]	0 [-0.03, 0.02]
Complexity low risk (high)	**0.14** **[0.11, 0.18]**	**0.13** **[0.09, 0.17]**	-0.02 [-0.04, 0.01]	**-0.03** **[-0.05, -0.01]**
EV difference	**0** **[0, 0]**	**0** **[0, 0]**	**0** **[0, 0]**	**0** **[0, 0]**
Higher EV equals higher Risk (True)	0 [-0.03, 0.03]	0.02 [-0.02, 0.05]	-0.01 [-0.03, 0.01]	0 [-0.02, 0.02]

C.6 Computational Modeling: Specification of Other Diffusion Parameters

When describing the computational model in the main text we focused on the definition of the drift rate δ, since this parameter is used to test our hypotheses about age differences in the link between attention and choice. The drift diffusion model has further parameters, which are described below.

C.6.1 Boundary Separation

Because δ is defined based on a comparison between the options—that is, it tracks the relative evidence in favor of one option over the other option—the model has a relative choice boundary. That is, evidence in favor of one option has to exceed evidence in favor of the other option by a threshold amount. The parameter α captures how much excess evidence in favor of one option over the other option is required to make a choice. Higher values on the parameter α indicate greater conservatism, and—all else remaining equal—entail longer RTs. The parameter α is estimated for each participant. Since the behavioral analyses show that participants took more time under higher option complexity, the α parameter could vary across different levels of option complexity. Otherwise, α could not vary across trials.

C.6.2 Response Bias

The parameter γ defines the starting point of the accumulation process, that is, potential response biases that exist before information on the options is actively processed. The response bias is conventionally referred to as β. We avoided this conventional notation to avoid confusion, since we refer to coefficients on the drift rate as β. We use the letter γ instead to refer to the response bias. As participants had no information about the options prior to trial onset, and the presentation side of high and low risk options on screen was randomized across trials and participants, we fixed γ at .5. Hence, the two response boundaries were at equal distance from the starting point. Note that forcing this parameter to be constant across conditions and trials allows for a stronger test of the architecture of the diffusion model (Lewandowsky & Farrell, 2018).

C.6.3 Non-decision Time

The non-decision time τ accounts for the component of the RT that is not spent deliberating about the options but, for instance, on stimulus encoding, memory access, or implementing a motor response (cf. Ratcliff & Tuerlinckx, 2002). The parameter τ is estimated for each participant, but does not vary by trial. This is because τ, by definition, should be independent of the evaluation and comparison of the options, and the factors shaping these processes (which may vary across trials). Moreover, as in the case of the bias parameter, forcing this parameter to be constant across conditions and trials allows for a stronger test of the model's architecture (Lewandowsky & Farrell, 2018).

C.7 Computational Modeling: Results in Choices Between Safe and Risky Options

Here we provide tables of the coefficients and 95% posterior intervals for the GLMER analysis testing for age differences (Table C.9) and effects of option complexity (Table C.10) on the different components of the drift rate, in choices between safe and risky options. The estimates are depicted conditional on the complexity of risky options in Figure C.2.

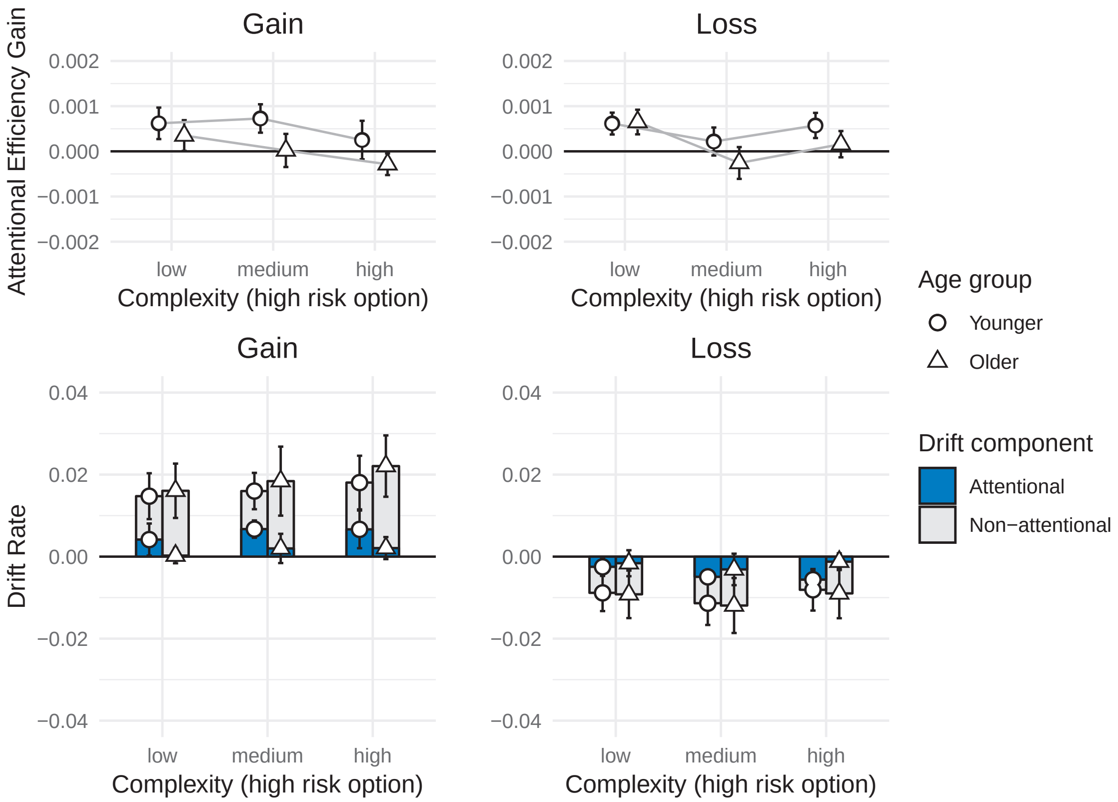

Figure C.2: Parameter estimates from the computational model in choices between safe and risky options, conditional on the complexity of safe options. Top panel: Estimates for attentional gains in processing efficiency $\beta_{gaze:EV,j}$. Bottom Panel: Estimates for the drift rate. The total height of the stacked bars represents the overall drift towards the safe option. The overall drift consists of the attentional drift $\delta_{attention}$ and the non-attentional baseline drift $\delta_{baseline}$. The relative impact of these components on the overall drift—that is, overall risk preferences—is color-coded.

Table C.9: GLMER Results on Age Differences in Parameter Estimates from Computational Modeling. How do Attentional Efficiency Gains, Attentional Drift and Baseline Drift Differ between Younger and Older Adults, in Choices between Safe and Risky Options, in each Domain and Condition? GLM Coefficients and 95% Posterior Intervals

	Complexity of Safe Option (Gains)			Complexity of Safe Option (Losses)		
Outcome	Low	Medium	High	Low	Medium	High
Attentional Efficiency Gains						
Intercept (Younger)	**0.00078** **[0.00049, 0.00106]**	3e-04 [-0.00015, 0.00074]	**0.00032** **[5e-05, 0.00058]**	**0.00065** **[0.00037, 0.00092]**	**0.00037** **[1e-05, 0.00072]**	**0.00046** **[9e-05, 0.00084]**
Older	**-0.00085** **[-0.00127, -0.00045]**	**-0.00067** **[-0.00132, -4e-05]**	-2e-04 [-0.00058, 0.00015]	**-0.00066** **[-0.00104, -0.00027]**	-1e-05 [-5e-04, 5e-04]	7e-05 [-0.00046, 0.00059]
Attentional Drift						
Intercept (Younger)	**0.01292** **[0.01009, 0.0156]**	**0.00514** **[0.00275, 0.00753]**	0.00139 [-0.00069, 0.00352]	**-0.00993** **[-0.01194, -0.00805]**	**-0.00289** **[-0.0049, -0.00093]**	-0.00093 [-0.00338, 0.00163]
Older	**-0.01018** **[-0.01441, -0.00605]**	-0.00119 [-0.00455, 0.0021]	-0.00128 [-0.00421, 0.00176]	**0.00843** **[0.00567, 0.01116]**	0.00111 [-0.00181, 0.00398]	-0.00168 [-0.00523, 0.00181]
Baseline Drift						
Intercept (Younger)	**0.00902** **[0.00395, 0.01424]**	**0.00802** **[0.00228, 0.0136]**	**0.01174** **[0.00657, 0.01732]**	0.00123 [-0.00316, 0.00562]	-0.00427 [-0.00974, 0.00106]	**-0.00988** **[-0.01471, -0.00499]**
Older	**0.01477** **[0.00798, 0.02226]**	**0.01257** **[0.00403, 0.0206]**	-0.00098 [-0.00881, 0.00686]	**-0.00947** **[-0.01591, -0.00301]**	-0.00176 [-0.00939, 0.00586]	0.00109 [-0.0057, 0.00839]

	Complexity of Risky Option (Gains)			Complexity of Risky Option (Losses)		
Outcome	Low	Medium	High	Low	Medium	High
Attentional Efficiency Gains						
Intercept (Younger)	**0.00059** **[4e-04, 0.00079]**	**0.00053** **[0.00032, 0.00073]**	**0.00057** **[0.00038, 0.00076]**	**0.00048** **[3e-04, 0.00066]**	**0.00048** **[0.00031, 0.00064]**	**0.00047** **[3e-04, 0.00064]**
Older	**-0.00056** **[-0.00085, -0.00028]**	**-0.00049** **[-0.00078, -2e-04]**	**-0.00054** **[-0.00083, -0.00027]**	**-0.00032** **[-0.00056, -7e-05]**	**-0.00029** **[-0.00053, -7e-05]**	**-0.00028** **[-0.00054, -5e-05]**
Attentional Drift						
Intercept (Younger)	**0.01041** **[0.0077, 0.013]**	**0.0043** **[0.00236, 0.00622]**	0.00142 [-0.00125, 0.00405]	**-0.00846** **[-0.01052, -0.00644]**	**-0.00247** **[-0.00419, -0.00079]**	-0.00175 [-0.00373, 0.00041]
Older	**-0.00602** **[-0.00968, -0.00216]**	**-0.00355** **[-0.00639, -0.00074]**	-0.00103 [-0.00483, 0.00276]	**0.00584** **[0.0029, 0.00876]**	0.00145 [-0.00099, 0.00391]	-1e-04 [-0.00313, 0.00293]
Baseline Drift						
Intercept (Younger)	**0.01038** **[0.00734, 0.01345]**	**0.01053** **[0.00739, 0.01353]**	**0.01039** **[0.0073, 0.01345]**	**-0.00509** **[-0.00789, -0.00217]**	**-0.0051** **[-0.00797, -0.00239]**	**-0.00509** **[-0.00785, -0.00223]**
Older	**0.00764** **[0.00362, 0.01211]**	**0.00703** **[0.0025, 0.01135]**	**0.00696** **[0.0025, 0.01145]**	-0.00261 [-0.00671, 0.00143]	-0.00267 [-0.00664, 0.00146]	-0.00262 [-0.00665, 0.00133]

Table C.10: GLMER Results on Effects of Complexity on Parameter Estimates from Computational Modeling. How does the Manipulation of Option Complexity Affect attentional Efficiency Gains, the Attentional Drift and the Baseline Drift, in Younger and Older Adults, in Choices between Safe and Risky Options? GLM Coefficients and 95% Posterior Intervals

	Attentional Efficiency Gains		Attentional Drift		Baseline Drift	
Domain	Younger	Older	Younger	Older	Younger	Older
Gains						
Intercept	**0.00079** **[0.00043, 0.00115]**	-8e-05 [-0.00042, 0.00026]	**0.01293** **[0.01028, 0.01561]**	**0.00275** **[0.00012, 0.0052]**	**0.009** **[0.00472, 0.01347]**	**0.02387** **[0.01743, 0.02996]**
Complexity Safe (Medium)	**-0.00048** **[-0.00098, -1e-05]**	-0.00029 [-0.00078, 0.00018]	**-0.00779** **[-0.01145, -0.00395]**	0.00123 [-0.00234, 0.00482]	-0.00098 [-0.00706, 0.00458]	-0.00336 [-0.0124, 0.00589]
Complexity Safe (High)	-0.00048 [-0.00098, 2e-05]	0.00019 [-0.00028, 0.00067]	**-0.01154** **[-0.01528, -0.00768]**	-0.00259 [-0.00613, 0.00109]	0.00264 [-0.00343, 0.00842]	**-0.0129** **[-0.02202, -0.00376]**
Losses						
Intercept	**0.00065** **[0.00033, 0.00098]**	-1e-05 [-0.00035, 0.00034]	**-0.00994** **[-0.01193, -0.008]**	-0.00155 [-0.00402, 0.00095]	0.00111 [-0.00375, 0.00628]	**-0.00834** **[-0.01314, -0.00325]**
Complexity Safe (Medium)	-0.00028 [-0.00076, 0.00018]	0.00036 [-0.00012, 0.00083]	**0.00707** **[0.00435, 0.0098]**	-0.00025 [-0.00375, 0.00331]	-0.00535 [-0.01238, 0.00173]	0.00229 [-0.00484, 0.0091]
Complexity Safe (High)	-0.00021 [-0.00066, 0.00025]	**0.00053** **[4e-05, 0.00102]**	**0.00904** **[0.00634, 0.01186]**	-0.00107 [-0.0046, 0.00245]	**-0.01092** **[-0.0179, -0.00403]**	-0.00042 [-0.0078, 0.00678]

	Attentional Efficiency Gains		Attentional Drift		Baseline Drift	
Domain	Younger	Older	Younger	Older	Younger	Older
Gains						
Intercept	**0.00062** **[0.00025, 0.00098]**	**0.00035** **[2e-05, 0.00067]**	**0.00275** **[2e-05, 0.00526]**	4e-04 [-0.00197, 0.00272]	**0.01065** **[0.00715, 0.01422]**	**0.01582** **[0.0091, 0.02245]**
Complexity Risky (Medium)	0.00011 [-0.00042, 0.00064]	-0.00034 [-0.00077, 0.00014]	**0.00394** **[0.00033, 0.00753]**	0.00234 [-0.00087, 0.00575]	-0.00139 [-0.00681, 0.00377]	0.00057 [-0.00872, 0.01]
Complexity Risky (High)	-0.00037 [-9e-04, 0.00015]	**-0.00064** **[-0.0011, -0.00016]**	**0.004** **[0.00047, 0.00757]**	0.00184 [-0.00127, 0.00524]	0.00067 [-0.00439, 0.0055]	0.0043 [-0.00497, 0.01355]
Losses						
Intercept	**0.00062** **[0.00033, 0.00089]**	**0.00065** **[0.00033, 0.00094]**	-0.00173 [-0.00354, 0.00013]	-0.001 [-0.00314, 0.00122]	**-0.00636** **[-0.01076, -0.00216]**	**-0.00754** **[-0.01289, -0.00224]**
Complexity Risky (Medium)	**-4e-04** **[-8e-04, -2e-05]**	**-0.00091** **[-0.00131, -0.00047]**	**-0.0032** **[-0.00591, -0.00052]**	-0.0022 [-0.00537, 8e-04]	-7e-05 [-0.00622, 0.00622]	-0.00123 [-0.00866, 0.0063]
Complexity Risky (High)	-5e-05 [-0.00042, 0.00035]	**-0.00049** **[-0.00091, -6e-05]**	**-0.0043** **[-0.00688, -0.00168]**	-0.00031 [-0.00347, 0.00263]	0.00383 [-0.00209, 0.01007]	-9e-05 [-0.00768, 0.00744]

C.8 Computational Modeling: Posterior Predictive Behavior in Choices Between Two Risky Options

Here we provide more information on the computational modeling results for choices between two risky options. Like in choices between safe and risky options, we evaluated whether the computational model could reproduce the patterns found in the data by inspecting posterior predictive choice behavior and RTs. To obtain posterior predictives we simulated a synthetic version of our experiment, in the rwiener function from the RWiener package (Wabersich & Vandekerckhove, 2014), using the subject level posterior mean estimates for all parameters and the original experimental task materials and fixation patterns. The simulated behavior for choices between two risky options is displayed in Figure C.3. Comparing the posterior predictive choice behavior to the original data (cf. Figure C.1) shows that the model reproduced the key behavioral regularities appropriately: Options were chosen less when they became more complex in the domain of gains, and RTs increased with complexity in both domains. The model also reproduces the interaction between age group and option complexity in the domain of gains.

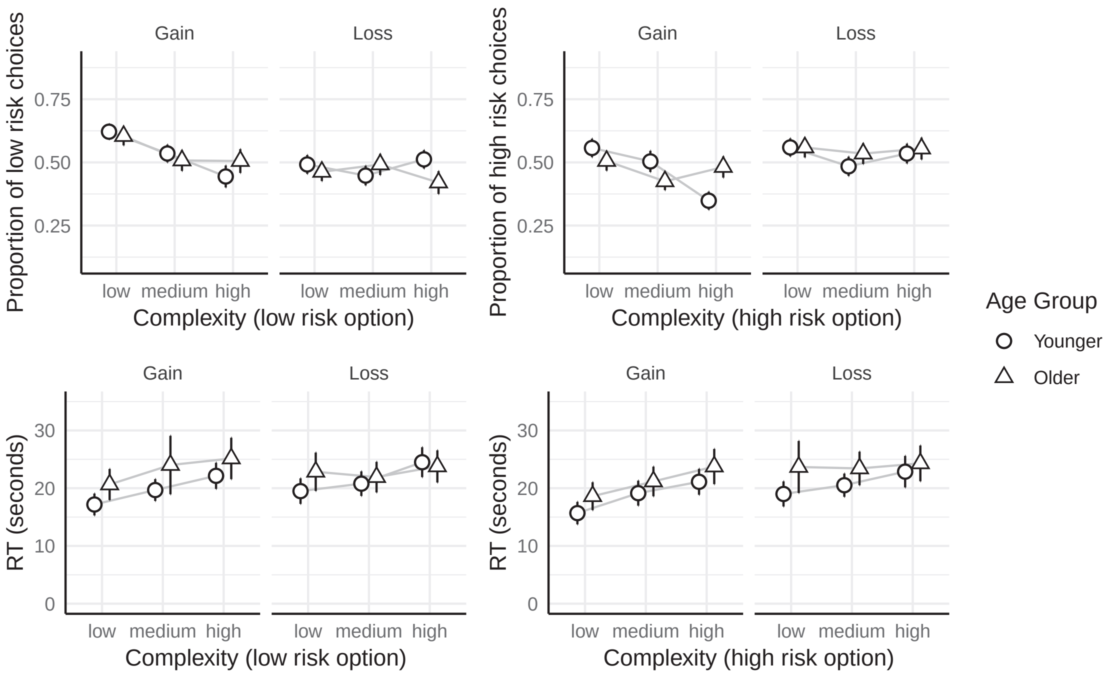

Figure C.3: Posterior predictive choice probabilities and RTs for choices between two risky options.

C.9 Computational Modeling: Results in Choices Between Two Risky Options

We also conducted parameter inference on the components of the drift rate, like in choices between safe and risky options. Here we provide Tables of the coefficients and 95% posterior intervals for the GLMER analysis testing for age differences (Table C.11) and effects of option complexity (Table C.12) on the different components of the drift rate, in choices between two risky options.

Table C.11: How do Attentional Efficiency Gains, Attentional Drift and Baseline Drift Differ between Younger and Older Adults, in Choices between two Risky Options, in each Domain and Condition? GLM Coefficients and 95% Posterior Intervals

	Complexity of Low Risk Option (Gains)			Complexity of Low Risk Option (Losses)		
Outcome	Low	Medium	High	Low	Medium	High
Attentional Efficiency Gains						
Intercept (Younger)	**0.00013** **[4e-05, 0.00021]**	8e-05 [-4e-05, 0.00021]	-3e-05 [-0.00014, 9e-05]	6e-05 [-5e-05, 0.00015]	1e-04 [-5e-05, 0.00025]	9e-05 [-3e-05, 0.00022]
Older	-4e-05 [-0.00017, 7e-05]	-5e-05 [-0.00023, 0.00013]	-6e-05 [-0.00024, 1e-04]	-1e-05 [-0.00015, 0.00013]	-0.00014 [-0.00034, 7e-05]	-0.00014 [-0.00032, 4e-05]
Attentional Drift						
Intercept (Younger)	0.00018 [-0.00052, 0.00087]	8e-05 [-0.00095, 0.00103]	-0.00085 [-0.00193, 0.00015]	-2e-05 [-0.00086, 0.00083]	-6e-04 [-0.00163, 0.00041]	-2e-04 [-0.00107, 0.00066]
Older	0.00018 [-0.00076, 0.00117]	**-0.00146** **[-0.00283, -7e-05]**	0.00115 [-0.00031, 0.00264]	-0.00072 [-0.00192, 0.00044]	0.00067 [-0.00082, 0.00204]	0.00082 [-0.00044, 0.00208]
Baseline Drift						
Intercept (Younger)	**0.00763** **[0.00671, 0.00859]**	**0.0035** **[0.00229, 0.00476]**	**-0.00178** **[-0.00321, -0.00036]**	**-0.001** **[-0.00173, -0.00031]**	**-0.00238** **[-0.00361, -0.00114]**	0.00029 [-0.00102, 0.00157]
Older	**-0.00182** **[-0.00314, -5e-04]**	**-0.00354** **[-0.0053, -0.00189]**	0.00114 [-0.00088, 0.00312]	-0.00082 [-0.00182, 0.00017]	0.00128 [-0.00054, 0.00302]	**-0.0028** **[-0.00464, -0.00101]**
	Complexity of High Risk Option (Gains)			Complexity of High Risk Option (Losses)		
Outcome	Low	Medium	High	Low	Medium	High
Attentional Efficiency Gains						
Intercept (Younger)	5e-05 [-1e-05, 0.00011]	5e-05 [-1e-05, 0.00011]	4e-05 [-1e-05, 1e-04]	6e-05 [-1e-05, 0.00013]	6e-05 [0, 0.00012]	6e-05 [-1e-05, 0.00012]
Older	-5e-05 [-0.00014, 3e-05]	-7e-05 [-0.00015, 2e-05]	-4e-05 [-0.00012, 5e-05]	-2e-05 [-0.00012, 7e-05]	-5e-05 [-0.00014, 3e-05]	-5e-05 [-0.00014, 4e-05]
Attentional Drift						
Intercept (Younger)	-2e-04 [-0.00101, 0.00057]	-0.00035 [-0.00119, 0.00049]	**-0.0017** **[-0.00275, -0.00061]**	1e-04 [-0.001, 0.00124]	-0.00072 [-0.00167, 0.00021]	-0.00028 [-0.00119, 0.00062]
Older	0.00026 [-8e-04, 0.00135]	0.00047 [-7e-04, 0.00165]	0.00032 [-0.00111, 0.00187]	-0.00081 [-0.00242, 0.00079]	0.00027 [-0.00109, 0.00164]	0.00107 [-0.00022, 0.00235]
Baseline Drift						
Intercept (Younger)	**0.00265** **[0.00183, 0.00346]**	**0.00271** **[0.0019, 0.00354]**	**0.00267** **[0.00187, 0.00348]**	**-0.00098** **[-0.00166, -3e-04]**	**-0.00101** **[-0.00171, -0.00034]**	**-0.00096** **[-0.00163, -0.00029]**
Older	-0.00111 [-0.00229, 6e-05]	**-0.00122** **[-0.00235, -6e-05]**	-0.00112 [-0.00238, 4e-05]	-0.00079 [-0.00178, 0.00017]	-8e-04 [-0.00176, 0.00018]	-0.00084 [-0.0018, 0.00016]

Table C.12: How does the Manipulation of Option Complexity Affect Attentional Efficiency Gains, the Attentional Drift and the Baseline Drift, in Younger and Older Adults, in Choices between two Risky Options? GLM Coefficients and 95% Posterior Intervals

	Attentional Efficiency Gains		Attentional Drift		Baseline Drift	
Domain	Younger	Older	Younger	Older	Younger	Older
Gains						
Intercept	**0.00013** **[2e-05, 0.00023]**	8e-05 [-4e-05, 0.00021]	0.00019 [-0.00046, 0.00084]	0.00036 [-0.00052, 0.00127]	**0.0076** **[0.00652, 0.00875]**	**0.0058** **[0.00452, 0.00704]**
Complexity Low Risk (Medium)	-4e-05 [-0.00019, 1e-04]	-5e-05 [-0.00022, 0.00012]	-0.00013 [-0.00119, 0.00085]	**-0.00174** **[-0.00315, -0.00043]**	**-0.00409** **[-0.0057, -0.0025]**	**-0.00583** **[-0.00766, -0.00397]**
Complexity Low Risk (High)	-0.00015 [-3e-04, 0]	**-0.00018** **[-0.00036, -1e-05]**	-0.001 [-0.00209, 4e-05]	-9e-05 [-0.00151, 0.00122]	**-0.00937** **[-0.01098, -0.00781]**	**-0.00642** **[-0.00826, -0.00467]**
Losses						
Intercept	6e-05 [-4e-05, 0.00015]	5e-05 [-1e-04, 2e-04]	-3e-05 [-0.00076, 0.00069]	-0.00073 [-0.00176, 0.00028]	-0.00101 [-0.00203, 2e-05]	**-0.00185** **[-0.00303, -0.00072]**
Complexity Low Risk (Medium)	5e-05 [-9e-05, 0.00018]	-9e-05 [-3e-04, 0.00013]	-0.00055 [-0.00163, 0.00054]	0.00076 [-0.00077, 0.00236]	-0.00132 [-0.0028, 0.00011]	0.00073 [-0.00081, 0.00241]
Complexity Low Risk (High)	4e-05 [-1e-04, 0.00017]	-1e-04 [-3e-04, 0.00012]	-0.00017 [-0.00121, 0.00089]	0.00135 [-8e-05, 0.00279]	0.00131 [-0.00014, 0.00281]	-0.00065 [-0.00227, 0.00101]
	Attentional Efficiency Gains		Attentional Drift		Baseline Drift	
Domain	Younger	Older	Younger	Older	Younger	Older
Gains						
Intercept	-2e-05 [-0.00012, 8e-05]	3e-05 [-9e-05, 0.00014]	**-0.00118** **[-0.00211, -0.00021]**	**-0.00178** **[-0.00292, -0.00071]**	**-0.00143** **[-0.00258, -0.00032]**	**-0.00239** **[-0.00352, -0.00129]**
Complexity High Risk (Medium)	8e-05 [-6e-05, 0.00022]	-0.00011 [-0.00027, 5e-05]	0.00021 [-0.00103, 0.00146]	**0.00213** **[0.00069, 0.00358]**	**0.00262** **[0.001, 0.00428]**	**0.00675** **[0.00516, 0.00833]**
Complexity High Risk (High)	0.00014 [-1e-05, 0.00028]	3e-05 [-0.00014, 0.00019]	0.00114 [-1e-04, 0.00238]	**0.0018** **[0.00043, 0.00321]**	**0.00964** **[0.00806, 0.01126]**	**0.00473** **[0.00307, 0.00632]**
Losses						
Intercept	**0.00012** **[2e-05, 0.00023]**	-2e-05 [-0.00016, 0.00012]	-0.00048 [-0.0013, 0.00035]	0.00015 [-0.00113, 0.00144]	**-0.0021** **[-0.0031, -0.00107]**	**-0.00187** **[-0.00308, -0.00068]**
Complexity High Risk (Medium)	-2e-05 [-0.00017, 0.00012]	3e-05 [-0.00015, 0.00022]	8e-05 [-0.00104, 0.00119]	1e-05 [-0.00172, 0.00176]	**0.00473** **[0.00327, 0.00619]**	0.0013 [-0.00042, 0.00296]
Complexity High Risk (High)	**-0.00017** **[-0.00032, -3e-05]**	0.00013 [-6e-05, 0.00032]	0.00055 [-0.00058, 0.00168]	-0.00087 [-0.00263, 0.00093]	-0.00128 [-0.00275, 0.00015]	-0.00096 [-0.00266, 0.00069]

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D | Supplemental Materials to Chapter 5

D.1 The Impact of Other Diffusion Parameters on Behavior

In the aDDM, evidence in favor of the safe option DV_{safe} and evidence in favor of the risky option DV_{risky} evolve over time. On time-steps t where the safe option is attended to DV_{safe} and DV_{risky} evolve according to

$$\begin{aligned} DV_{safe}(t) &= DV_{safe}(t-1) + d * \theta_{attended} * o_{safe} + \epsilon \\ DV_{risky}(t) &= DV_{risky}(t-1) + d * \theta_{unattended} * o_{i,risky} + \epsilon \end{aligned} \tag{D.1}$$

and on time-steps t where the risky option is attended to DV_{safe} and DV_{risky} evolve according to

$$\begin{aligned} DV_{safe}(t) &= DV_{safe}(t-1) + d * \theta_{unattended} * o_{safe} + \epsilon \\ DV_{risky}(t) &= DV_{risky}(t-1) + d * \theta_{attended} * o_{i,risky} + \epsilon \end{aligned} \tag{D.2}$$

with $\epsilon \sim \mathcal{N}(0, \sigma^2)$. In the simulation reported in the main text the diffusion parameters $\theta_{unattended}$ and σ were set to specific invariant values. Here we show how the behavior of the aDDM changes if these parameters are varied, and how this affects the mapping between aDDM and CPT's probability-weighting function.

D.1.1 Methods

Scaling the level of noise

The parameter σ defines the standard deviation of the Gaussian noise ϵ in the evidence accumulation process, with higher values of σ indicating higher levels of noise. For the simulations reported in the main text σ was set to 0.075. Here we show how the aDDM behaves in a noise-free process, and under higher levels of noise, by simulating data with σ also set to 0 and 0.15.

Scaling the attentional weights

The parameter $\theta_{unattended}$ captures that evidence in favor of an option evolves at a slower rate on steps where the other option is inspected. In the main text $\theta_{unattended}$ was set to .5, such that evidence evolves twice as fast when an option is attended, compared to when it is unattended. Here we show how the aDDM behaves when varying $\theta_{unattended}$, by simulating data with $\theta_{unattended}$ set to 0 and 1.

Simulation

Information search and choice patterns were simulated for the same 150 decision problems offering a safe and a risky option, which were also used in the main text. The aDDM was used as a generative model. The probability p_{t_s} of inspecting the safe option on each step was varied along the same 11 levels also used in the main text. $\theta_{unattended}$ was varied between 0, 0.5 and 1. The level of noise σ was varied between 0, 0.075 and 0.15. These values for all three parameters were permuted with each other to obtain 99 possible parameter combinations. For each of these 99 combinations choices of 25 synthetic subjects on all 150 pairs of gambles were simulated, resulting in 99 data-sets with 25×150 choices each.

D.1.2 Results

Proportion of Safe Choices

Figure D.1 shows how the different diffusion parameters affect the tendency to choose the safe option.

For $\theta_{unattended} = 1$ evidence for an option accumulates at equal rates, irrespective of whether the option is currently attended or not. In this case the aDDM reduces to a standard DDM. Hence the relative attention p_{t_s} has no effect on choice behavior. If $\theta_{unattended}$ is smaller than 1, attentional biases do affect choice behavior: Greater relative attention p_{t_s} to the safe option increases the proportion of safe choices, and this effect is stronger for lower values of $\theta_{unattended}$. This is because the accumulation of evidence for the unattended option slows down more severely for lower values of $\theta_{unattended}$. How does the noise σ affect these behavioral patterns? In the noise-free process with $\sigma = 0$, $\theta_{unattended}$ and p_{t_s} have the most pronounced effect on safe option choices. Under higher levels of noise, these effects are dampened, due to greater non-systematicity in the data.

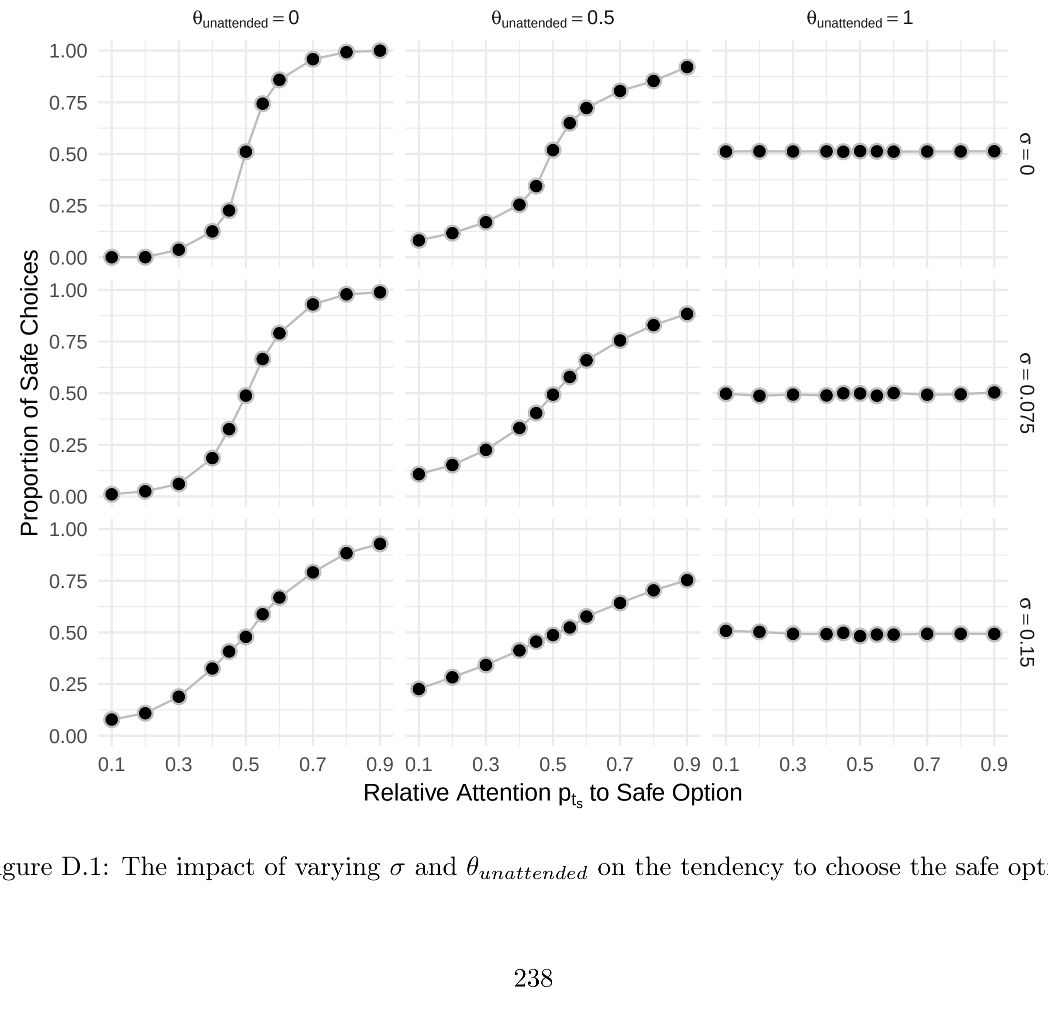

Figure D.1: The impact of varying σ and $\theta_{unattended}$ on the tendency to choose the safe option.

Decision Quality

Figure D.2 shows how the different diffusion parameters affect the tendency to choose the option with the higher EV, that is, maximizing behavior or decision quality.

For $\theta_{unattended} = 1$ the aDDM reduces to a standard DDM. Hence attentional biases p_{t_s} have no effect on choice behavior, and thus decision quality. If this standard DDM process is noise free (with $\sigma = 0$), decision quality is immaculate: The model always chooses the option with the higher EV. Under higher levels of noise σ decision quality decreases. This is because non-systematic errors perturb maximizing behavior.

If $\theta_{unattended}$ is smaller than 1, attentional biases do affect decision quality: Decision quality decreases with more asymmetric attention $p_{t_s} \neq .5$, because the evidence accumulation process does not reflect differences between the options' values in an objective manner anymore. Instead the representation of differences between the options is distorted by attentional biases. Hence, under extreme attentional biases, performance drops to chance level. The systematic effect of asymmetric attention on decision quality is most pronounced in the noise free process with $\sigma = 0$. This is because in this case, decision quality for the unbiased process (with $p_{t_s} = .5$) is the highest, and can hence decrease most dramatically due to attentional biases.

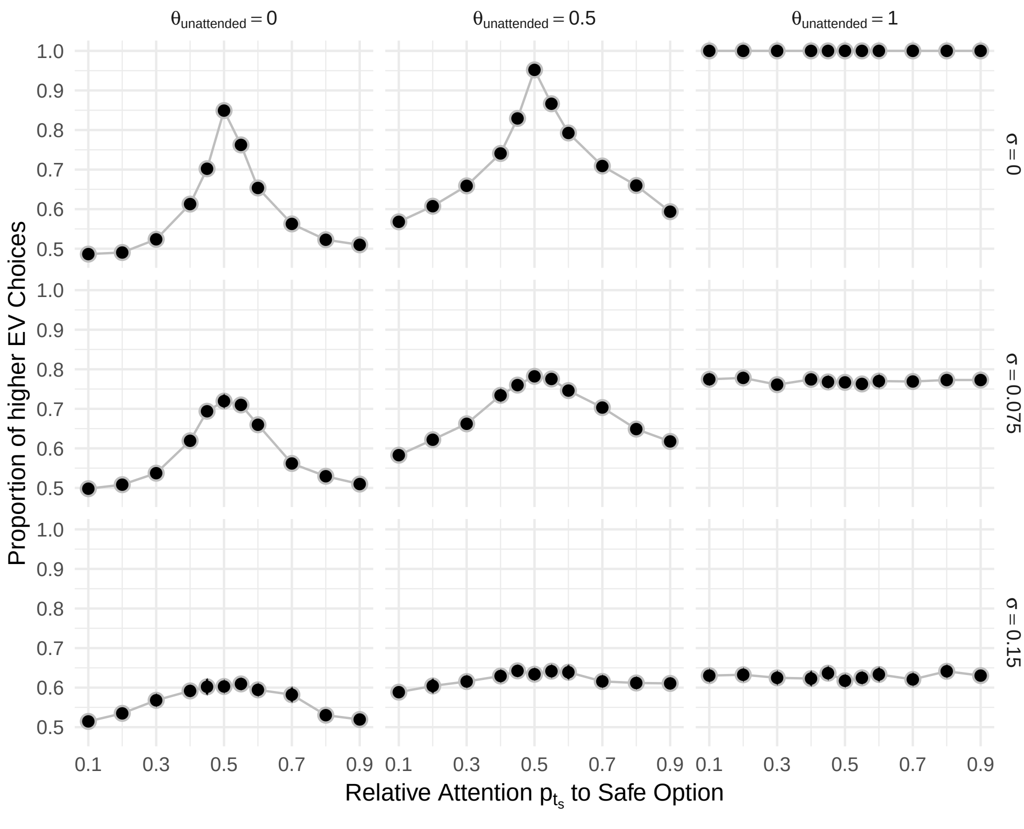

Figure D.2: The impact of varying σ and $\theta_{unattended}$ on decision quality.

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Response Time

Figure D.3 shows how the different diffusion parameters affect the RTs.

For $\theta_{unattended} = 1$ the relative attention p_{t_s} has no effect on RTs. The longest RTs emerge if the process with $\theta_{unattended} = 1$ is also noise free ($\sigma = 0$). Remember that in this case, decision quality is maximal. That is, the simulation illustrates a speed accuracy trade-off: more precise, noise-free and unbiased processes achieve the highest performance, but take the most time.

If $\theta_{unattended}$ is smaller than 1, attentional biases do affect RTs: RTs decrease with more extreme attentional biases $p_{t_s} \neq .5$, because an evidence accumulation process biased towards one option can reach the corresponding boundary faster. Note that, again, this decrease in RT is associated with a decrease in decision quality, illustrating a speed-accuracy trade-off. The level of noise in the process modulates the effects of $\theta_{unattended}$ on RTs.

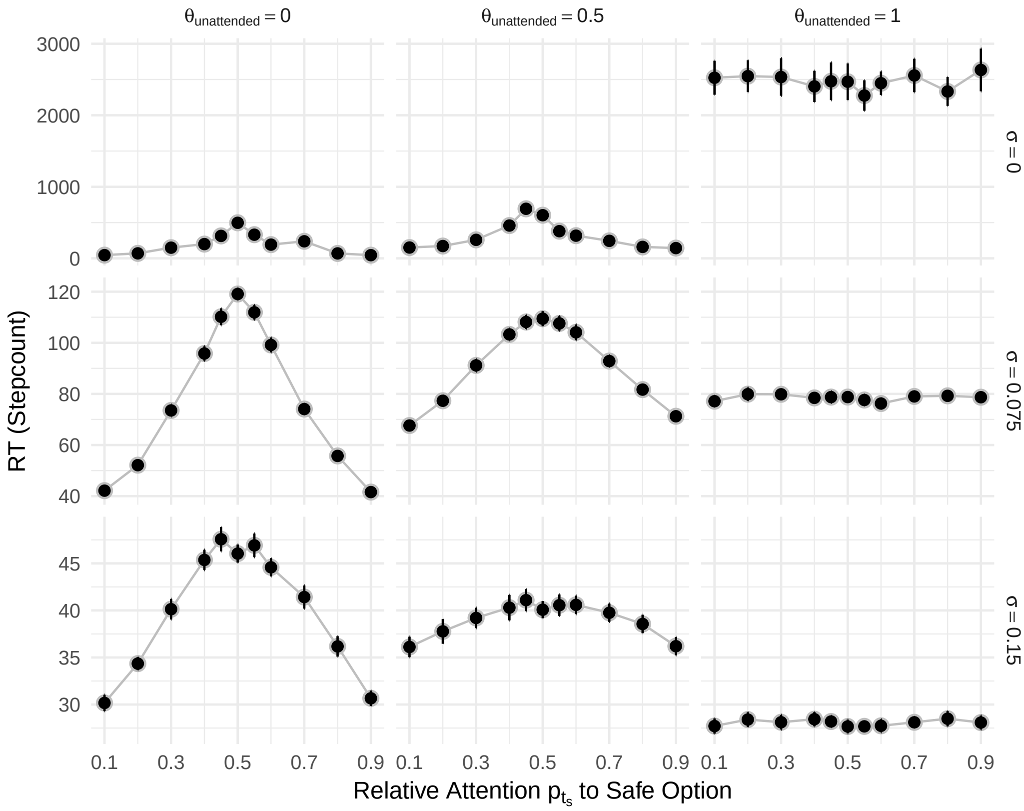

Figure D.3: The impact of varying σ and $\theta_{unattended}$ on response times.

Summary

Varying the parameters σ and $\theta_{unattended}$ in the aDDM modulates the severity of the effect of option specific attentional biases on all three aspects of choice behavior (risky choice, decision quality and RTs). However, the key regularities—more extreme attentional biases towards either option increase the tendency to choose this option, and thereby decrease both decision quality and RTs—are very robust. These key regularities only disappear in the extreme case, where the aDDM reduces to a standard DDM, and attention does not affect behavior.

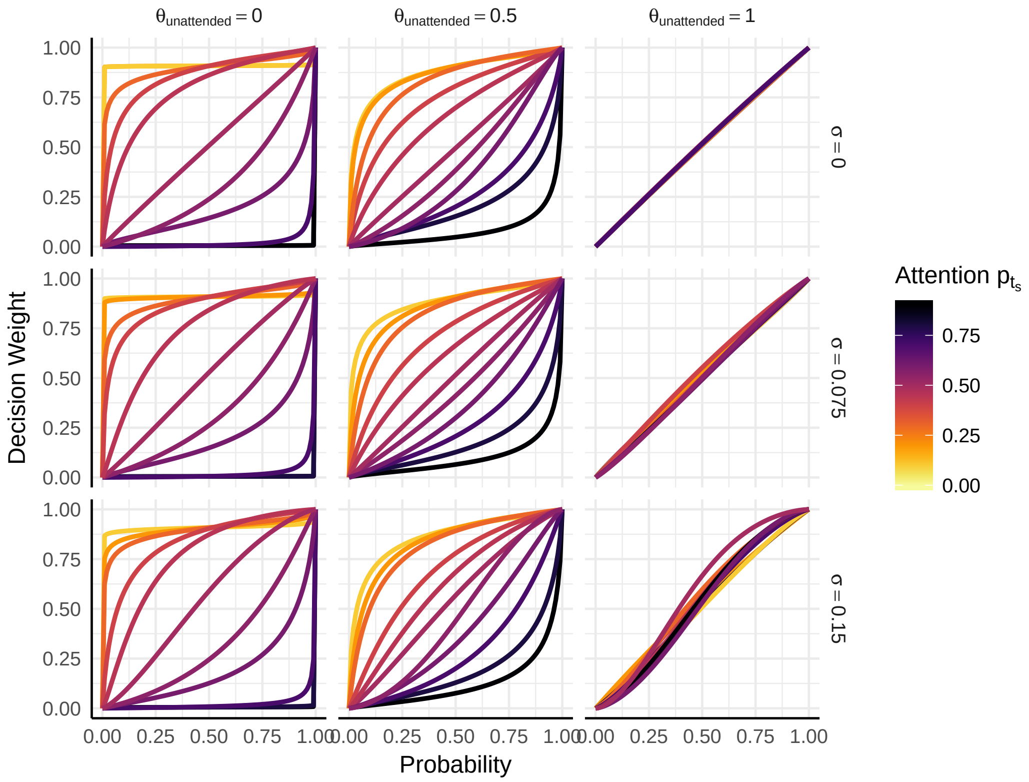

Figure D.4: Probability-weighting function by Goldstein & Einhorn (1987), based on CPT fitted to data sets generated with varying diffusion parameters (p_{t_s}, σ and $\theta_{unattended}$) .

D.2 Extension to Choices Between Two Risky Options

To test whether the link between attentional biases in the aDDM and probability weighting in CPT can be extended to choice problems offering two risky options, information search and choice patterns were simulated for 150 decision problems offering two risky options, using the aDDM, while varying the attentional bias. A hierarchical Bayesian implementation of CPT was fitted to the simulated choices for each level of attentional bias in the generative process.

D.2.1 Structure of the Lottery Problems

150 pairs of risky options A and B were generated using the following procedure: Both risky outcomes were sampled from a uniform distribution ranging from 0 to 10, and rounded to 2 digits. The higher outcome in each gamble is labelled o_{high} and the lower outcome o_{low}. The probability p_{high} of the higher outcome was sampled from a uniform distribution ranging from 0 to 1, and the probability of the lower risky outcome was defined as $p_{low} = 1 - p_{high}$. The gamble on each pair with the lower probability p_{high} was named gamble A, and the other gamble was named gamble B. We eliminated dominated gamble pairs where both outcomes of one option were larger than both outcomes of the other option. We randomly generated gamble pairs in this manner until we had obtained 75 pairs on which option A had the higher EV, and 75 pairs on which option B had the higher EV. The resulting 150 gamble pairs were used to generate simulated choices.

D.2.2 Simulation

The aDDM was used as a generative model. The probability p_{t_s} of inspecting option B on each step was systematically varied from .1 to .9 in increments of .1. To increase the resolution of our analysis for moderate attentional biases we added two additional levels for p_{t_s} in the mid-range (at .45 and .55), resulting in a total of 11 levels of attentional bias. The parameter $\theta_{unattended}$ was set to 0.5, such that evidence for each option accumulated at half the speed when it was unattended (versus attended). The noise parameter σ was set to 0.075. For each level of p_{t_s} choices of 25 synthetic subjects on all 150 pairs of gambles were simulated, resulting in 11 data-sets with 25×150 choices each.

D.2.3 Modeling

Each of the 11 data-sets was fitted separately in four hierarchical Bayesian implementations of CPT. The four models only differed in terms of the weighting function, using either the function by Goldstein and Einhorn (1987), Prelec (1998, both variants), or Tversky and Kahneman (1992). In the hierarchical models, each synthetic subject had a separate value on each parameter, and these subject-level parameters were informed by a group-level distribution. Parameter inference (presented in the results section) was based on the group-level posterior estimates.

D.2.4 Results: Synthetic Choice Behavior

We first describe the impact of attentional biases in the aDDM on choice behavior, in terms of choosing option B (the option that received more or less attention), decision quality and response times. All three features are analysed with Bayesian Mixed Regression models implemented using the rstanarm package in R (Goodrich et al., 2018), and all models include random intercepts for each synthetic subject. We evaluate the credibility of the tested fixed effects by inspecting whether the 95%CIs on the regression coefficients include zero.

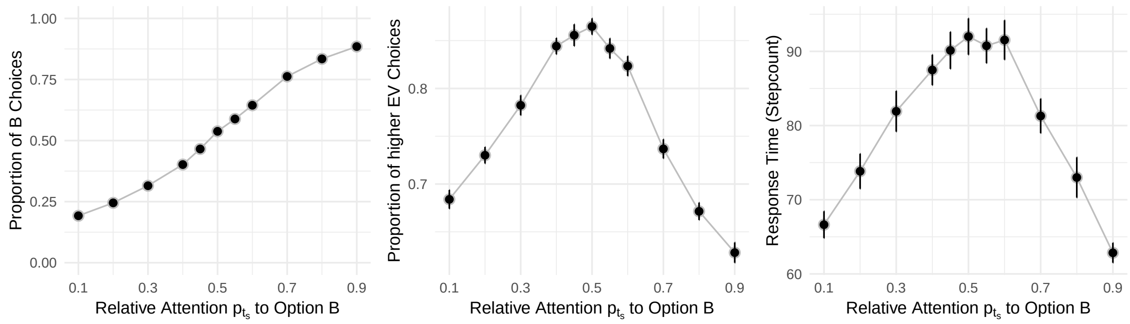

Figure D.5: Preference for option B, decision quality, and response times observed in the choice patterns generated in the aDDM, conditional on the attentional bias to the option B p_{t_s}.

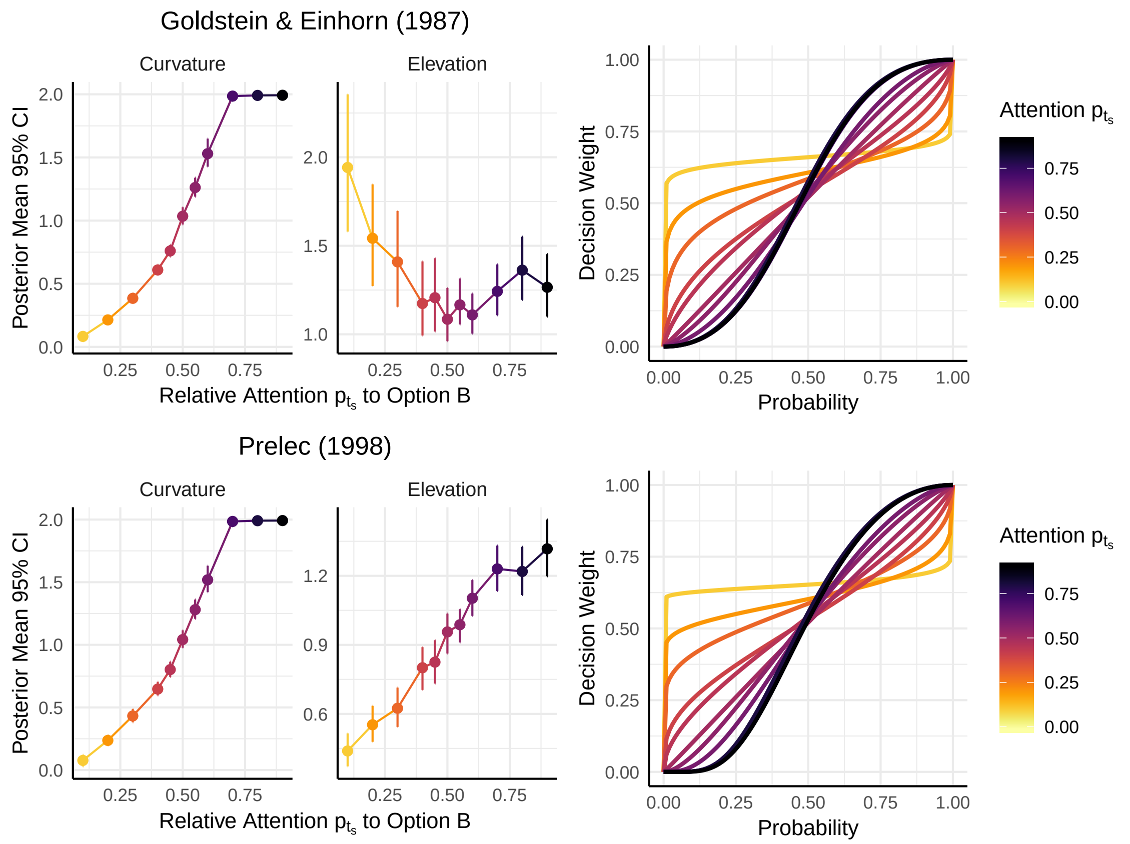

Figure D.6: Parameter estimates and weighting functions for the two-parameter weighting functions for choices between two risky options. The color gradient represents the proportion of time spent attending to option B. Darker colors represent a greater attentional bias to the option B.

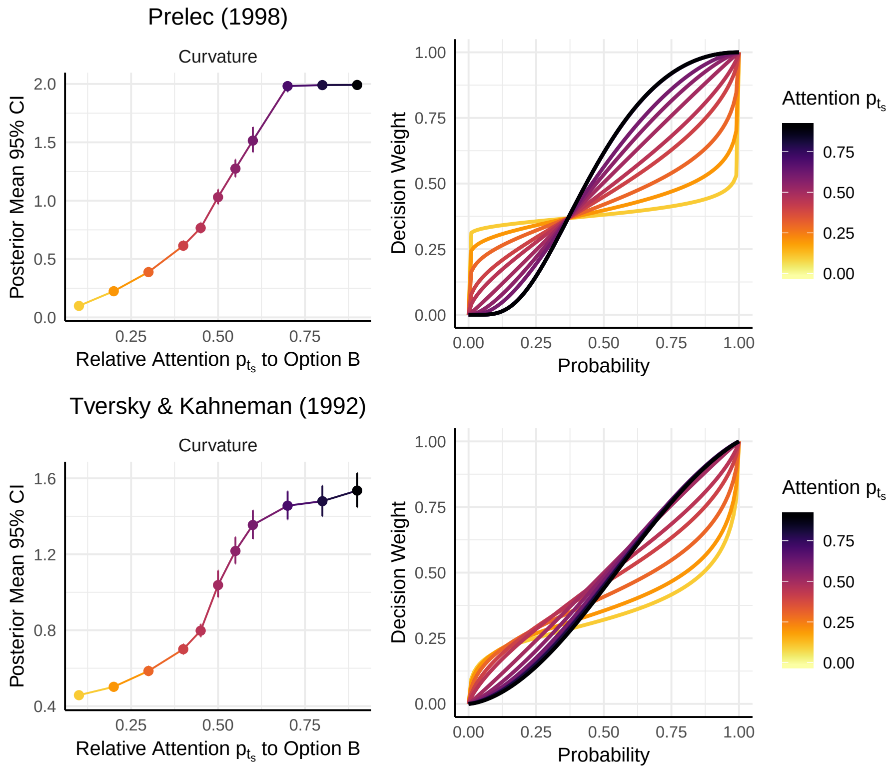

Figure D.7: Parameter estimates and weighting functions for the one-parameter weighting functions for choices between two risky options. The color gradient represents the proportion of time spent attending to option B. Darker colors represent a greater attentional bias to the option B.

Option B choices

The proportion of choices of option B increased with the attentional bias towards option B (cf. left panel of Figure D.5). The statistical credibility of this effect was corroborated in a Bayesian logistic mixed regression on the choice of option B as the outcome variable. The model included the relative attention to option B p_{t_s} as a fixed predictor. There was a strong credible effect of attention to option B on the tendency to choose that option ($\beta = 4.51$, 95% CI $[4.40, 4.62]$).

Decision quality

The proportion of choices of the option with the higher EV (decision quality) decreased with increasingly extreme attentional biases, regardless which option received more attention (cf. middle panel of Figure D.5). The statistical credibility of this effect was corroborated in a Bayesian logistic mixed regression of decision quality as the outcome variable.. The model included the absolute magnitude of the attentional bias (calculated as the absolute deviation of p_{t_s} from .5) as a fixed predictor. There was a negative credible effect of the magnitude of the attentional bias on decision quality ($\beta = -3.18$, 95% CI $[-3.35 - 3.02]$): As pointed out earlier, introducing attentional biases impairs maximization performance, because the probability of choosing the option that receives more attention increases, irrespective of whether this option is objectively preferable.

Response times

The response times (RT, measured as the number of steps in the diffusion process until the boundary is hit) decreased with increasingly extreme attentional biases, regardless which option received more attention (cf. right panel of Figure D.5). The statistical credibility of this effect was corroborated in a Bayesian mixed regression of RT as the outcome variable. The model included the absolute magnitude of the attentional bias (calculated as the absolute deviation of p_{t_s} from .5) as a fixed predictor. There was a negative credible effect of the magnitude of the attentional bias on RT ($\beta = -72.23$, 95% CI $[-77.73, -66.72]$): Stronger attentional biases, regardless towards which option, allow the model to make faster choices. However, as established previously, this increased speed comes at the cost of lower decision quality.

D.2.5 Results: Parameter Inference

Parameter inference for two-parameter weighting functions

Did the mapping between attentional biases and weighting function parameters extend to choices between two risky options? In the two-parameter weighting functions (Goldstein & Einhorn, 1987; Prelec, 1998) a greater attentional bias p_{t_s} towards the option with the higher probability p_{high} (option B) is reflected in a less elevated and more strongly S-shaped weighting function (cf. Figure D.6). S-shaped weighting functions with a low elevation tend to overweight higher probabilities more than lower probabilities. Hence, because $p_{B,high} > p_{A,high}$, the decision weight $\pi_{B,high}$ tends to increase the valuation of option B more than the decision weight $\pi_{A,high}$ increases the valuation of option A. Such weighting functions thus shift the comparison between option A and B in favor of option B—and can thus account for the attentional bias towards option B.

Parameter inference for one-parameter weighting functions

In the one-parameter weighting functions (Prelec, 1998; Tversky & Kahneman, 1992) a greater attentional bias p_{t_s} towards the option with the higher probability p_{high} is reflected in a more strongly S-shaped weighting function (i.e. higher values on the curvature parameter γ, cf. Figure D.7). This is due to the same mechanism as in the case of the two-parameter weighting functions. S-shaped weighting functions tend to overweight higher probabilities more than lower probabilities. Hence, because $p_{B,high} > p_{A,high}$, the decision weight $\pi_{B,high}$ amplifies the valuation of option B more than the decision weight $\pi_{A,high}$ amplifies the valuation of option A. Thereby it shifts the comparison between option A and B in favor of option B—and achieves the same effect as the attentional bias towards option B.

D.2.6 Conclusion

The link between attentional biases in the aDDM and decision weights in CPT extends to choices between two risky options. In this case especially the curvature of weighting functions affects the comparison between the two options, by differentially modulating the decision weights assigned to outcomes with higher or lower probabilities. Consequently, the curvature is very potent in accounting for attentional biases, even in the less flexible one-parametric weighting functions.

D.3 Details on CPT Modeling of Empirical Data

We fitted two versions of hierarchical Bayesian CPT to the DfE data from Wulff et al. (2018). The models were designed to be sensitive to capturing the relationships between attentional biases and probability weighting parameters which we identified in the simulation analysis. To this end, the trial-level parameters δ and γ could co-vary with the empirically observed sampling bias towards the safe option on each trial. The empirical sampling bias towards the safe option $X_{bias,s,i}$ on each trial i and in each subject s was measured as the proportion of samples from the safe option minus .5. Hence a positive (negative) sampling bias expresses a bias towards the safe (risky) option, and a sampling bias of 0 means that the both options were sampled equally often.

D.3.1 CPT with Prelec's Weighting Function

Based on our results in the simulation and recovery analyses for the weighting function by Prelec (1998), we expected a negative linear relationship between greater attention towards the safe option and the curvature parameter γ, and a positive linear relationship between greater attention towards the safe option and the elevation parameter δ. To test for these effects in the empirical data, we regressed the weighting function parameters on the empirical sampling bias towards the safe option $X_{bias,s,i}$. That is, the trial-level elevation and curvature parameters for the weighting function by Prelec (1998) were defined as a linear combination of a subject-specific intercept and a subject-specific slope on the sampling bias observed on each trial:

$$\delta_{s,i} = \beta_{intercept,s,\delta} + \beta_{bias,s,\delta} * X_{bias,s,i} \tag{D.3}$$

$$\gamma_{s,i} = \beta_{intercept,s,\gamma} + \beta_{bias,s,\gamma} * X_{bias,s,i} \tag{D.4}$$

Hence a subject-specific slope $\beta_{bias,s,\delta}$ of zero indicates that the empirical sampling bias did not affect the elevation in subject s. A negative subject-specific slope $\beta_{bias,s,\delta}$ indicates that the participant's elevation was lower on trials where the safe option was sampled predominantly, compared to trials where the risky option was sampled predominantly. Defining the parameters in this manner and estimating the β coefficients allows us to explicitly measure the impact of attentional biases on the shape of the weighting function.

D.3.2 CPT with Goldstein and Einhorn's Weighting Function

Based on our results in the simulation and recovery analyses for the weighting function by Goldstein and Einhorn (1987), we expected a negative linear relationship between relative amount of attention to the safe option and the elevation parameter δ, and an inverse-U shaped relationship between the relative amount of attention towards the safe option and the curvature parameter γ. To test for these effects in the empirical data, we regressed the weighting function parameters on the empirical sampling bias towards the safe option. That is, the trial-level elevation and curvature parameters for the weighting function by Goldstein and Einhorn (1987) were defined as a linear combination of a subject-specific intercept and a subject-specific slope on the sampling bias observed on each trial:

$$\delta_{s,i} = \beta_{intercept,s,\delta} + \beta_{bias,s,\delta} * X_{bias,s,i} \tag{D.5}$$

$$\gamma_{s,i} = \beta_{intercept,s,\gamma} + \beta_{bias,s,\gamma} * X^2_{bias,s,i} \tag{D.6}$$

Note that this model can measure a quadratic relationship between sampling bias and γ, in line with the inverse-U shaped relationship observed in the simulations, due to the quadratic term $X^2_{bias,s,i}$. Otherwise, the parameters can be interpreted in the same manner as the corresponding parameters for the model with Prelec's weighting function.

D.3.3 Hierarchical Structure of the Models

Both models were based on a hierarchical parameter structure: The subject-specific coefficients $\beta_{intercept,s}$ are informed by paper-level distributions (for individual papers included in the meta-analysis by Wulff et al., 2018), which were in turn informed by a top level distribution across all papers. This modeling approach mimics the random-effects structure commonly used in meta-analyses, and meets the concern expressed by Wulff et al. (2018) that aggregating across CPT parameters from methodologically diverse studies would risk producing average parameters of questionable value. The model was fitted to the experienced probabilities, such that potential effects of attentional biases on γ and δ can not be trivially attributed to the over- or undersampling of particular events relative to their objective probability.

D.4 Quantifying Distortions in Probability Weighting

In the main text, we provided an intuition how nonlinear weighting functions can make risky options appear more or less attractive, while maintaining a stable valuation for safe options, such that the comparison between safe and risky options is either shifted in favor of or against risky options. Here we address how we can quantify whether a particular weighting function, given specific parameter settings, distorts the valuation of risky options.

To reiterate, the total valuation V_{risky} of a risky option in CPT is

$$V_{risky} = \pi_{high} * [v(o_{high}) - v(o_{low})] + v(o_{low}) \tag{D.7}$$

Under linear probability weighting π_{high} equals the objective probability p_{high} such that CPT reduces to EU. Under nonlinear probability weighting π_{high} can be smaller or larger than p_{high}, such that the risky option appears less or more attractive than under linear weighting. Whether a particular nonlinear probability-weighting function w makes a particular risky option appear less or more attractive than a linear weighting function can be quantified by taking the difference between $\pi_{high} - p_{high}$. If this difference is smaller than zero, the nonlinear weighting function makes risky options with the probability p_{high} appear less attractive, and if the difference is larger than zero it makes such risky options appear more attractive. The difference $\pi_{high} - p_{high}$ can thus quantify to which extent the weighting function w distorts the valuation of the set of risky options with the particular probability p_{high}.

To measure how the weighting function w affects the valuation of risky options more generally, in a manner that is not conditioned on the particular probability p_{high}, we can integrate the difference between each objective probability and the assigned decision weight across the entire probability range $[0, 1]$:

$$\pi_{distortion} = \int_0^1 \big[w(p) - p\big]\, dp \tag{D.8}$$

One thereby obtains the difference between the area under the diagonal (i.e. linear weighting) and the area under the nonlinear weighting function w. How can this difference $\pi_{distortion}$ be interpreted? For weighting functions w with $\pi_{distortion} = 0$ the amount of overweighting and the amount of underweighting cancel each other out, when considering the entire probability range. That is, individual risky options may appear more or less attractive under this weighting function than under linear weighting—depending on their probability p_{high}. However, viewed on average across the entire set of conceivable risky options (with p_{high} distributed uniformly across all probabilities in $[0, 1]$), a weighting function w with $\pi_{distortion} = 0$ does not systematically make risky options appear more or less attractive.

For weighting functions with $\pi_{distortion} < 0$ the amount of underweighting exceeds the amount of overweighting, when considering the entire probability range. This could, for instance, be the case if the weighting function runs below the identity line across most of the probability range. Hence, averaged across the entire set of conceivable risky options, such weighting functions tend to make risky options appear less attractive. Generally speaking, they tend to shift the comparison between risky and safe options in favor of the safe option. This qualifies them to mimic attentional biases towards the safe over the risky option.

For weighting functions with $\pi_{distortion} > 0$ the amount of overweighting exceeds the amount of underweighting, when considering the entire probability range. This could, for instance, be the case if the weighting function runs above the identity line across most of the probability

Table D.1: Range of $\pi_{distortion}$ of Risky Options' Valuation under each of the Weighting Functions in CPT, Compared to EU, for Specific Ranges of the Parameters δ and γ

	$V_{risky,CPT} < V_{risky,EU}$		$V_{risky,CPT} > V_{risky,EU}$	
Weighting Function	Range of $\pi_{distortion}$	Parameter range	Range of $\pi_{distortion}$	Parameter range
Goldstein and Einhorn (1987)	$[-0.50, 0]$	$\delta < 1$	$[0, 0.41]$	$\delta > 1$
Prelec (1998)				
- two-parameter	$[-0.50, 0]$	$\delta \lessapprox 1$	$[0, 0.50]$	$\delta \gtrapprox 1$
- one-parameter (with $\delta = 1$)	$[-0.13, 0]$	$\gamma < 1$	$[0, 0.05]$	$\gamma > 1$
Tversky and Kahneman (1992)	$[-0.5, 0]$	$\gamma < 1$	none	none

range. Hence, averaged across the entire set of conceivable risky options, such weighting functions tend to make risky options appear more attractive. They hence tend to shift the comparison between risky and safe options in favor of the risky option. This qualifies them to mimic attentional biases towards the risky over the safe option.

D.4.1 Can Different Weighting Functions Distort the Valuation of Risky Options?

Our argument posits that a weighting function's capacity to mimic attentional biases depends on its capacity to shift the comparison between safe and risky options either against, or in favor of, risky options, by making them appear less or more attractive. To evaluate whether the four different weighting functions discussed in this paper have this capacity, we inspect the range of $\pi_{distortion}$ across the entire parameter space of γ and δ. If this range includes values smaller than zero, the weighting function can assume shapes that make risky options appear less attractive. If it includes values larger than zero, the weighting function can assume shapes that make risky options appear more attractive.

Two-parameter weighting functions

First we consider the two-parameter weighting functions by Goldstein and Einhorn (1987) and Prelec (1998): Across all combinations of the parameters δ in the range $[0, 10]$ and γ in the range [0,2] the values of $\pi_{distortion}$ vary within $[-.49, .41]$ for the weighting function by Goldstein & Einhorn (1987), and within $[-.50, .49]$ for the weighting function by Prelec (1998). Hence, there are parameter combinations for both weighting functions under which $\pi_{distortion}$ is smaller than zero, meaning that they are capable of systematically making risky options appear less attractive. There are also parameter combinations for both functions under which $\pi_{distortion}$ is larger than zero, meaning that both weighting functions are also capable of systematically making risky options appear more attracitve. Therefore both weighting functions should be able to mimic attentional biases both towards the risky and towards the safe option.

One-parameter weighting functions

Next, we consider the weighting functions which are governed only by the curvature γ, ranging within [0,2]: In the one-parameter variant of Prelec's weighting function $\pi_{distortion}$ varies within $[-.13, .05]$ across the entire range of γ. Thus it is capable of making risky options appear both less and more attractive. However, the range of $\pi_{distortion}$ is considerably narrower compared to the two-parameter form. This indicates that the one-parameter form may be less capable of mimicking extreme option-specific attentional biases, especially towards the risky option, which may require a stronger distortion of risky options' valuation.

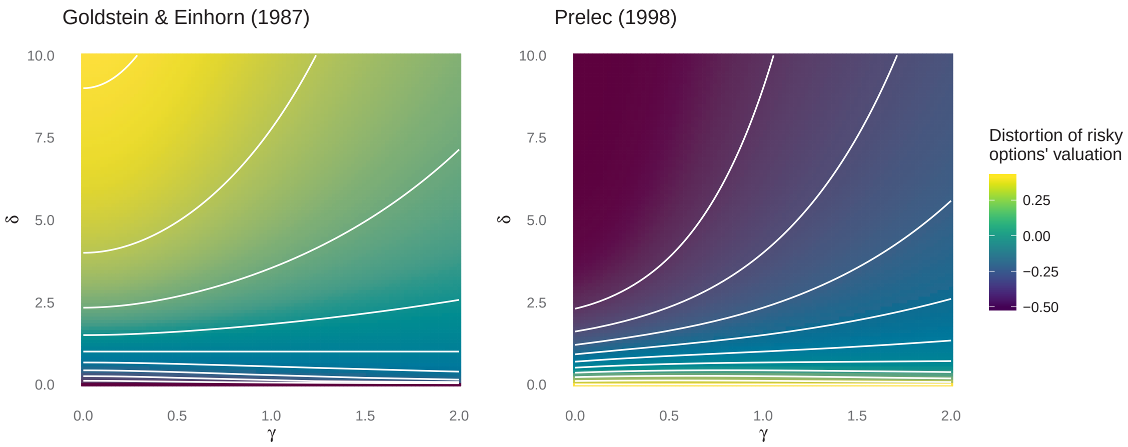

Figure D.8: Distortion of risky options' valuation due to the weighting function across the parameter range of γ and δ for the two-parameter weighting functions by Goldstein and Einhorn (1987, left panel) and Prelec (1998, right panel).

In the one-parameter weighting function by Tversky and Kahneman (1992) $\pi_{distortion}$ varies in [-0.5, 0] across the entire parameter range of γ. That is, this weighting function can make risky options appear less attractive, but—because $\pi_{distortion}$ never exceeds 0—it can not make them appear more attractive. Hence this weighting function can shift the comparison between risky and safe options against risky options, but not in their favor. Therefore we expect this weighting function to be sensitive to attentional biases towards the safe option but not towards the risky option.

D.4.2 Under which Parameter Settings do Weighting Functions Distort the Valuation of Risky Options, and How?

Besides evaluating whether a weighting function is at all capable of shifting the comparison between risky and safe options, we can also identify under which specific parameter combinations this is the case. This allows us to formulate specific hypotheses regarding how each weighting function is expected to mimic the option-specific attentional biases in the aDDM. To this end we mapped π_{total} on the parameter space of δ and γ for all four weighting functions.

Two-parameter weighting functions

Figure D.8 illustrates the distortion of risky options' valuation $\pi_{distortion}$ under each combination of the parameters δ and γ for the two-parameter weighting functions by Goldstein and Einhorn (1987) and Prelec (1998) . The color gradient represents $\pi_{distortion}$: Brighter (/darker) colors indicate parameter combinations under which risky options appear more (/less) attractive.

In Goldstein and Einhorn's (1987) weighting function the elevation parameter δ is the main determinant of $\pi_{distortion}$. Risky options appear more attractive if $\delta > 1$ and less attractive if $\delta < 1$. Hence we expect that attentional biases to the risky option are reflected in larger values of δ in the range $\delta > 1$, and that attentional biases to the safe option are reflected in smaller values of δ in the range $\delta < 1$. Moreover, given values of δ at a further distance from 1, lower values of the curvature γ entail a more extreme distortion of risky options' valuation (regardless whether positive or negative). Therefore, for more extreme attentional biases (whether in favor of the safe or the risky option), this weighting function may assume lower values of γ.

In the two-parameter variant of Prelec's (1998) weighting function, the elevation parameter

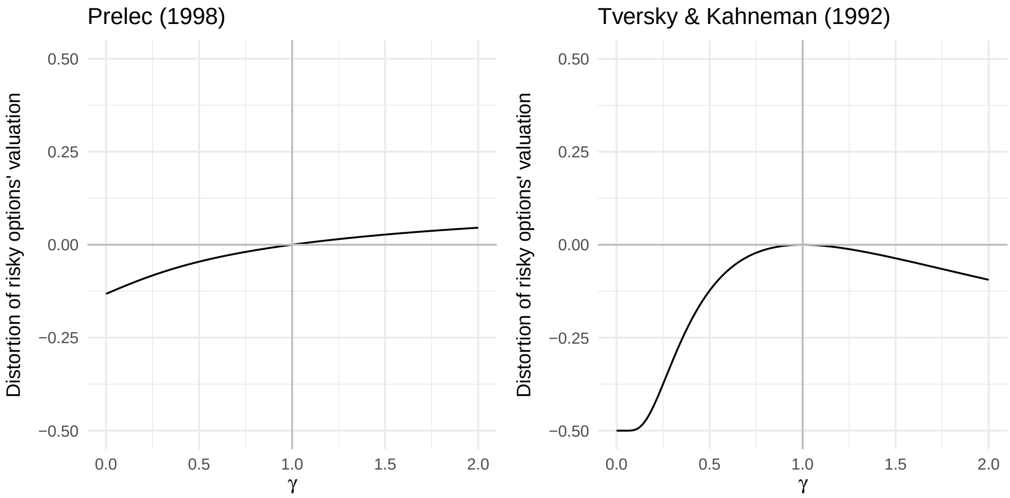

Figure D.9: Distortion of risky options' valuation due to the weighting function across the parameter range of γ for the one-parameter form of the weighting function by Prelec (1998, left panel) and the one-parameter weighting function by Tversky and Kahneman (1992, right panel).

δ is also the main determinant of $\pi_{distortion}$. Risky options appear less attractive under higher values of $\delta \gtrapprox 1$ and more attractive under lower values of $\delta \lessapprox 1$. Hence stronger attentional biases to the safe option may be mimicked in larger values of δ in the range $\delta \gtrapprox 1$, and that stronger attentional biases to the risky option may be reflected in smaller values of δ in the range $\delta \lessapprox 1$.[1] Moreover, as in the case of Goldstein & Einhorn's weighting function, given values of δ at a further distance from 1, lower values of the curvature γ amplify the distortion of risky options' valuation (regardless whether positive or negative). Therefore, given more extreme attentional biases (whether in favor of the safe or the risky option), this weighting function may assume lower values of γ.

One-parameter weighting functions

Next, let us consider the one-parameter weighting functions which are governed only by the curvature γ. The distortion of risky options' valuation $\pi_{distortion}$ under each value of γ for one-parameter variant of Prelec's weighting function and the weighting function by Tversky and Kahneman (1992) is illustrated in Figure D.9. Risky options appear less (/more) attractive if this black line (illustrating π_{total}) runs below (/above) the horizontal grey line (marking a the valuation under linear probability weighting). In both one-parameter weighting functions risky options are trated neutrally under $\gamma = 1$.

In the one-parameter variant of Prelec's weighting function, risky options are appear less attractive under $\gamma < 1$ and more attractive under $\gamma > 1$. Hence attentional biases to the safe option may be reflected in lower values of γ in the range $\gamma < 1$, and attentional biases to the risky option may be reflected in higher values of γ in the range $\gamma > 1$.

In the one-parameter weighting function by Tversky and Kahneman (1992) risky options appear less attractive under $\gamma < 1$, but they never appear more attractive. Hence we predict that attentional biases to the safe option are reflected in lower values of γ in the range $\gamma < 1$. Since π_{total} never exceeds zero, attentional biases to the risky option can not be mimicked by this

[1] In Prelec's weighting function, *lower* values of δ entail a *higher* elevation, while in Goldstein and Einhorn's weighting function, *higher* values of of δ entail a *higher* elevation. Thus, while in both cases risky options appear more attractive when the weighting function is more elevated, this feature is mapped on the parameter space differently, explaining the different direction of the color gradients in Figure D.8.

weighting function.

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List of Manuscripts

Chapters 2-5 of this dissertation have been prepared with co-authors as manuscripts for peer-reviewed journals. The chapters are however *not* identical to the versions of the manuscripts which were later published or submitted for peer-review.

- A later modified version of chapter 2 has been published as: Zilker, V., Hertwig, R., & Pachur, T. (2020). Age differences in risk attitude are shaped by option complexity. *Journal of Experimental Psychology: General. 149*(9), 1644–1683. Chapter 2 is a preprint version and not identical to the final published article! At the time this dissertation was submitted at the FU Berlin the article had not yet been published.

- A later modified version of chapter 3 has been submitted for peer-review: Zilker, V. & Pachur, T. (2020). *Does Option Complexity Contribute to the Framing Effect, Loss Aversion, and Delay Discounting in Younger and Older Adults?* Chapter 3 is a preprint version and not identical to the submitted manuscript!

- A later modified version of chapter 4 has been prepared for peer-review: Zilker, V. & Pachur, T. (2020). *Gaze amplifies value in decisions by younger but not older adults* Chapter 4 is a preprint version and not identical to the manuscript prepared for peer-review!

- A later modified version of chapter 5 has been submitted for peer-review: Zilker, V. & Pachur, T. (2020). *Nonlinear probability weighting can reflect attentional biases in sequential sampling.* Chapter 5 is a preprint version and not identical to the submitted manuscript!

Lebenslauf

Mein Lebenslauf wird aus Gründen des Datenschutzes in der elektronischen Fassung meiner Arbeit nicht veröffentlicht.

Declaration of Independent Work

I hereby declare that:

- I completed this doctoral thesis independently. Except where otherwise stated, I confirm that the work presented in this thesis is my own.
- Where information has been derived from other sources, I confirm that this has been indicated in the thesis.
- I have not applied for a doctoral degree elsewhere and do not have a corresponding doctoral degree.
- I have acknowledged the Doctoral Degree Regulations which underlie the procedure of the Department of Education and Psychology of Freie Universität Berlin, as amended on August 8th 2016.
- The principles of Freie Universität Berlin for ensuring good academic practice have been complied with.

Veronika Zilker
Berlin, 30. Juli 2019