An Ecological Perspective on Decisions under Risk: How the Structure of the Environment Shapes Information Processing

Doctoral thesis for obtaining the academic degree

Doctor of Natural Sciences (Dr. rer. nat.)

submitted by

Kevin Erik Tiede

at the

Universität Konstanz

Faculty of Sciences

Department of Psychology

Konstanz, 2021

Date of the Oral Examination:	January 20, 2022
First Reviewer:	Prof. Dr. Wolfgang Gaissmaier
Second Reviewer:	Prof. Dr. Urs Fischbacher
Third Reviewer:	Prof. Ellen Peters, PhD

Table of Contents

Acknowledgements vii
Summary ix
Zusammenfassung xi
Chapter 1: Synopsis 1
1.1 General Introduction 2
1.2 Research Paper 1: The Role of Choice Context in Risky Choice 6
1.3 Research Paper 2: The Trade-Off between the Costs and Benefits of Time 9
1.4 Research Paper 3: The Role of Cognitive Effort in Processing Medical Information 11
1.5 General Discussion 14
References 17
Chapter 2: The Role of Choice Context in Risky Choice 21
2.1 Introduction 23
2.2 Methods 31
2.3 Results 36
2.4 Discussion 43
2.5 Conclusion 45
References 46
Chapter 3: The Trade-Off between the Costs and Benefits of Time 49
3.1 Introduction 51
3.2 Results 55
3.3 General Discussion 62
3.4 Methods 65
References 71
Chapter 4: The Role of Cognitive Effort in Processing Medical Information 73
4.1 Introduction 75
4.2 Methods 79
4.3 Results 85
4.4 Discussion 90
4.5 Limitations 91
4.6 Conclusion 92
References 93

S1 Supplemental Materials to Chapter 2 95
S1.1 Pilot Study 95
S1.2 Choice Problems used in the Main Study 101
S1.3 Additional Analyses for Main Study 103
S1.4 Choice Problems used in the Pilot Study 109
References 111
S2 Supplemental Materials to Chapter 3 113
S2.1 Screenshot of Trial Screens 113
S3 Supplemental Materials to Chapter 4 117
S3.1 Description of Pilot Study 117
S3.2 Presentation Formats and Screenshots of Question Page 118
Author Contributions 121

Acknowledgements

A lot of people have accompanied and supported me during the development of this dissertation and have contributed to my research. Here, I want to take the opportunity to acknowledge these people, groups, and institutions and to thank them.

I have been privileged to work with amazing mentors and collaborators who have supported me and my research throughout my PhD. First and foremost, I want to thank you, Wolfgang, for working with me, sharing your knowledge and experience, and for giving me the opportunity to pursue my passion. I very have much enjoyed working with you. Thorsten, I have learned a lot during our collaboration and grew as researcher through our joint work. Thank you for having invited me to ARC and for supporting me and my research in various ways. Ellen, it has been a pleasure to work with you. Thank you for encouraging and supporting me and my research in all these years. I feel honored and grateful that you are reviewing this dissertation. Nika, thank you for sharing your expertise and experience with me and for your insightful ideas during our collaboration. Urs Fischbacher, I want to thank you not only for reviewing this dissertation, but also for leading the Graduate School of Decision Sciences.

During my PhD, I had the chance to be a permanent or temporary member of different labs. First of all, I want to thank the current and former members of the Social Psychology and Decision Sciences Lab who not only provided me with valuable feedback on my projects, but also made my time in Konstanz an even nicer experience. Simultaneously, the Graduate School of Decision Sciences was my second academic home port. During my time as a PhD student, I met many fellow PhD students who became my friends and who accompanied on this journey towards the PhD. Thank you for this amazing time and all your support. I also want to thank the Center for Adaptive Rationality at the Max Planck Institute for Human Development for inviting me to stay for six months and for welcoming me so warmly. Its nice and supportive researchers turned this research stay into a highly productive time and an unforgettable experience. Thank you also to the Cognitive and Affective Influences in Decision making (CAIDe) Lab at—back then—the Ohio State University for inviting me again for a research visit during my PhD. It has been so much fun to work with you.

Two people have contributed to making my time at the University of Konstanz easier and a lot more convenient. Kerstin, thank you so much for taking care of administrative issues and helping me out when I had open questions. Jutta, thank you for all your help and time during my PhD and the pleasant cooperation during my time as a student representative.

This research would not have been possible without the generous support by various institutions. I want to thank the Graduate School of Decision Sciences, the Social Psychology and Decision Sciences Lab, the Center for Adaptive Rationality at the Max Planck Institute for Human Development, and the Committee on Research (AFF) at the University of Konstanz for funding the studies for this dissertation. Further, I want to deeply thank the *Studienstiftung des deutschen Volkes* for supporting me as a person and researcher throughout the last three years. Its financial funding and non-financial support has allowed me to fully devote myself to pursuing my passion and has helped me to broaden my horizon.

Besides, there have been people who did not necessarily contribute to my research, but were essential to my well-being and happiness. First, I want to thank you, Mama, my biggest fan, for supporting and accompanying me not just through my PhD, but all the way leading up to this milestone in my life. Christopher and Caroline, you have made me laugh, have teased me, and have showed me your love—all of which gave me the strength to navigate through my PhD. Oma und Opa, ihr habt immer an mich geglaubt und mich auf meinem Lebensweg stets in vielfältiger Weise unterstützt. Dafür danke ich euch von ganzem Herzen.

Besides my family, I could always rely on friends and colleagues who supported me and who I could share the pleasant and less pleasant experiences of being a PhD student with. Tjaša, Tamara, Ruchira, Nico, Felix, Nathalie, Sophie, Miriam, and Alisa, I am happy to have met you and to have been able to spend so much time with you. You were also responsible for turning my years in Konstanz into an amazing time. Your support and friendship mean a lot to me. Fahima, Anna, and Jenny, thank you for your friendship and support—mostly from further away, but highly appreciated.

Lastly, I want to thank all 1636 participants who took part in the empirical studies of this dissertation.

Summary

When people make decisions, the consequences of their choices are often not certain, but rather choices can lead to different outcomes, each with a different probability. In such *decisions under risk*, choices have been shown to not only depend on the available options but also on the environment they are made in. This dissertation aims to provide further insights into how the *structure of the environment* influences *information processing* in decisions under risk. Thereby, it focuses on both the way people learn about information and time constraints as features of the environment and studies decisions under risk in the basic and an applied domain. Further, the projects of this dissertation go beyond the examination of choice behavior by also studying response times and by implementing computational modeling. Together, the three research papers aim to answer open questions regarding the role of the environment in decisions under risk.

In Research Paper 1, we study the role of choice context in decisions under risk. Previous research has shown that people seem to evaluate risky options differently depending on whether they learn about them from a summary description or from drawing sequential samples from the payoff distribution (i.e., through experience). However, it is unclear how the learning mode of the alternative option influences the evaluation of an option. When choosing between a described and an experienced option, are options also evaluated differently within a choice or rather jointly? To answer this question, we compared people's choice and search behavior in such a mixed condition with their behavior in a purely description- or experience-based condition. Using cumulative prospect theory to model choices and map people's subjective representations of outcome and probability information, we found evidence for a joint subjective representation of outcomes and probabilities which differed from that in the purely description-based and purely experience-based conditions. Finally, per-option search effort in the mixed condition was higher than in the purely experience-based condition and was sensitive to features of the described option. In conclusion, these findings highlight the role of choice context and, specifically, the reciprocal influence of options and their respective learning mode when people construct preferences in risky choice.

In Research Paper 2, we investigate how adaptively people trade off the costs and benefits of time when there are opportunity costs of time. When making choices, deliberation time is often costly but also promises to improve decision making. We investigate to what extent people respond to the costs and benefits of time adaptively. Using the drift diffusion model as a computational framework, we first determined with computer simulations how boundary separations should be adaptively set in order to maximize payoffs depending on the differences in options' value and the level of opportunity costs. Subsequently, we conducted three empirical experiments to study if people behave in accordance with the implications of the simulations. Across all experiments, participants did not adaptively take into account the level of opportunity costs and the differences in option value when making decisions. As a result, estimated boundary separations deviated from the optimal ones. In conclusion, people seem to have limited abilities to adjust their information processing adaptively to varying levels of value differences and opportunity costs.

In Research Paper 3, we study how much cognitive effort the processing of medical information requires depending on the presentation format. Previous research has shown that people understand the benefits and risks of treatments better when they are presented graphically (e.g., as icon arrays) than when numbers are used to communicate them. However, it is unclear how much cognitive effort the processing of the information in different formats requires and how effortful the comparison of treatments is if they are presented in different formats (i.e., inconsistently). The results of our preregistered experiment showed that answering knowledge questions with icon arrays (vs. numbers) required more cognitive effort. Further, having to compare inconsistently (vs. consistently) presented medications led to worse decisions and knowledge. In conclusion, our findings demonstrate the value of studying information processing in risk communication for understanding how, why, and under which conditions presentation formats improve medical decision making.

Studying decisions from different perspectives and in different domains, this dissertation provides comprehensive insights into the role of the environment in decisions under risk. By implementing novel research paradigms and using computational modeling, the research papers shed light onto how information processing is affected by the way information is presented and by constraints of time. More generally, the findings emphasize the importance of considering environmental features for a better understanding and ultimately improvement of human decision making.

Zusammenfassung

Wenn Menschen Entscheidungen treffen, sind deren Ausgänge oft nicht sicher. Vielmehr kann eine Entscheidung zu unterschiedlichen Ausgängen führen, die jeweils mit unterschiedlichen Wahrscheinlichkeiten auftreten. In solchen *Entscheidungen unter Risiko* hängen die getroffenen Entscheidungen nicht nur von den zur Verfügung stehenden Option ab, sondern auch von der Umwelt, in der sie getroffen werden. Das Ziel der vorliegenden Dissertation ist, weitere Erkenntnisse darüber zu ermöglichen, wie die *Struktur der Umwelt* die *Informationsverarbeitung* in Entschei-dungen unter Risiko beeinflusst. Dabei liegt der Schwerpunkt der Dissertation auf der Art und Weise, wie Menschen über Informationen lernen, und der verfügbaren Zeit als zwei Eigenschaften der Umwelt. Die Dissertation untersucht Entscheidungen unter Risiko im Grundlagenbereich und einem angewandten Bereich. Außerdem geht die Dissertation über die Untersuchung von Entscheidungsverhalten hinaus, indem sie Informationssuchverhalten und Reaktionszeiten analysiert und komputationale Modellierung einsetzt. Als Ganzes möchten die drei Forschungspapiere offene Fragen zur Rolle der Umwelt bei Entscheidungen unter Risiko beantworten.

Im ersten Forschungspapier untersuchen wir die Rolle des Kontexts in Entscheidungen unter Risiko. Frühere Forschung hat gezeigt, dass Menschen Optionen unterschiedlich evaluieren, je nachdem, ob sie über diese anhand von Beschreibungen lernen oder durch das sequenzielle Ziehen von Stichproben, also durch Erfahrung. Jedoch ist unklar, wie sich der Lernmodus der alternativen Option auf die Evaluation einer Option auswirkt. Werden die Optionen auch unterschiedlich evaluiert, wenn Menschen sich zwischen einer beschriebenen und einer erfahrenen Option entscheiden, oder werden diese in ähnlicher Weise evaluiert? Um diese Frage zu beantworten, verglichen wir das Entscheidungs- und Informationssuchverhalten in einer solchen Mixed-Bedingung mit dem Verhalten in Entscheidungen zwischen zwei beschriebenen oder zwei erfahrenen Optionen. Durch die Verwendung der *Cumulative Prospect Theory* zur Modellierung von Entscheidungen und Erfassung der subjektiven Repräsentation von Outcomes und deren Wahrscheinlichkeiten fanden wir Hinweise auf eine gemeinsame Repräsentation, die sich jedoch von der in rein beschreibungsbasierten oder rein erfahrungsbasierten Entscheidungen unterschied. Darüber hinaus war die Anzahl der gezogenen Stichproben in der Mixed-Bedingung größer als in der Bedingung mit zwei

erfahrenen Optionen und hing von Eigenschaften der beschriebenen Option ab. Insgesamt heben diese Befunde die Rolle des Entscheidungskontextes hervor sowie den gegenseitigen Einfluss der Optionen und deren Lernmodus bei der Entwicklung von Präferenzen in Entscheidungen unter Risiko.

Im zweiten Forschungspapier erforschen wir, wie adaptiv Menschen Kosten und Nutzen von Zeit in Entscheidungen unter Risiko mit Opportunitätskosten von Zeit abwägen. Wenn Menschen Entscheidungen treffen, ist Entscheidungszeit oft kostbar, jedoch kann sie auch Entscheidungen verbessern. Unsere Forschung untersucht, inwiefern Menschen adaptiv mit Kosten und Nutzen von Zeit umgehen. Wir verwendeten das Drift-Diffusionsmodell, um mithilfe von Computersimulationen zu bestimmen, wie der Abstand zwischen den Antwortschwellen in Abhängigkeit von den Wertunterschieden der Optionen und der Höhe der Opportunitätskosten sein sollte, um Gewinne zu maximieren. Anschließend führten wir drei empirische Experimente durch, um zu untersuchen, ob Menschen sich im Einklang mit den Ergebnissen der Simulation verhalten und adaptiv mit Zeit umgehen. Über alle Experimente hinweg haben Versuchspersonen die Unterschiede zwischen den Werten der Optionen nicht in adaptiver Weise berücksichtigt, sodass sich die geschätzten von den optimalen Schwellenabständen unterschieden. Zusammengefasst zeigen die Ergebnisse, dass Menschen nur begrenzte Fähigkeiten haben ihre Informationsverarbeitung in adaptiver Weise an an unterschiedliche Wertunterschiede und Opportunitätskosten anzupassen.

Im dritten Forschungspapier untersuchen wir, wie viel kognitive Leistung die Verarbeitung von medizinischen Informationen erfordert abhängig davon, wie sie dargestellt werden. Frühere Forschung hat gezeigt, dass Menschen die Nutzen und Risiken von Medikamenten besser verstehen, wenn sie grafisch (z.B. als *Icon Arrays*) dargestellt werden, als wenn sie mithilfe von Zahlen präsentiert werden. Es ist jedoch unklar, wie viel kognitive Leistung die Verarbeitung von Informationen je nach Format erfordert und wie kognitiv aufwändig der Vergleich von Medikamenten ist, die in verschie-denen Darstellungsformaten, also inkonsistent, präsentiert werden. Die Ergebnisse unseres präregistrierten Experiments zeigten, dass das Beantworten von Wissensfragen bei Icon Arrays mehr kognitive Leistungen erforderte als bei Zahlen. Zudem führte das Vergleichen von inkonsistent dargestellten Informationen zu schlechteren Leistungen in der Entscheidung und den Wissensfragen. Insgesamt verdeutlichen unsere Befunde, wie wichtig die Untersuchung der Informationsverarbeitung in der Risikokommunikation ist, um besser zu verstehen, wie, warum, und unter welchen Bedingungen bestimmte Präsentationsformate medizinische Entscheidungen verbessern können.

Indem diese Dissertation Entscheidungen aus unterschiedlichen Perspektiven und in verschiedenen Bereichen untersucht, bietet sie umfassende Erkenntnisse über die Rolle der Umwelt bei Entscheidungen unter Risiko. Durch die Verwendung von innovativen Forschungsmethoden und komputationaler Modellierung zeigt die Dissertation auf, wie Informationsverarbeitung davon beeinflusst wird, wie Menschen über Information lernen und wie verfügbar und kostspielig Zeit ist. Darüber hinaus heben die Befunde hervor, wie wichtig es ist, Eigenschaften der Umwelt zu berücksichtigen, um Entscheidungen besser verstehen und letztendlich auch verbessern zu können.

Chapter 1:

Synopsis

Kevin E. Tiede[1,2]

[1]Graduate School of Decision Sciences, University of Konstanz

[2]Department of Psychology, University of Konstanz

1.1 General Introduction

When people make decisions, the consequences of their choices are often not certain, but rather different outcomes are possible, each with a different likelihood. If a patient chooses between two medical treatments, it is usually not certain whether both or any of the treatments will improve the medical condition of that particular patient. However, based on clinical trials the patient often knows the chances of success of each treatment as well as the probabilities of experiencing side effects. Such decisions between options for which the probabilities of the possible outcomes are known are referred to as *decisions under risk* (Knight, 1921).

Decades of research have been spent studying how people make decisions under risk (Fox et al., 2015). While some general patterns have been detected regarding how people treat the possible outcomes of the options and their probabilities, the evaluation of options and the following choices have also been shown to greatly differ depending on how the environment is structured (e.g., the way information is provided; Hertwig et al., 2004). The goal of this dissertation is to extend the knowledge on the role of the environment in risky choice. Specifically, it focuses on the way people learn about information and time constraints as two features of the environment. Thereby, the three projects of this dissertation examine not only the choices people make in these decisions. Rather, all projects aim to uncover how people process the available information to arrive at their choices. As a whole, this dissertation provides important knowledge on how the environment shapes information processing in risky choice. This knowledge not only benefits our understanding of human decision making, but can also help to provide an environment which helps people to make better choices.

1.1.1 Decisions under Risk

To uncover the general principles of choice behavior, researchers often provide participants with two or more monetary lotteries and ask which one they prefer. These lotteries are supposed to represent options people decide between outside the lab, with the monetary outcomes reflecting the valuation of possible events and probabilities indicating their likelihoods.[1] For instance, participants may be asked to choose between “10€ for sure” or “10% to win 100€; 90% to win nothing”. When asked to choose between such lotteries, people demonstrate general patterns in how they deal with the

[1] Note that as probabilities are often not known in everyday life, stated probabilities may represent a simplification of these probabilities (Goldstein & Weber, 1997; Lopes, 1983).

outcomes and their probabilities. For instance, people seem to treat outcomes and probabilities as if they subjectively transformed them nonlinearly into subjective values and decision weights, respectively. As a result, people make choices as if small probabilities were larger than they actually are or to diminished sensitivity for increasing outcome values (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

Whereas monetary lotteries are a useful tool to study the basic principles of choice behavior, it is necessary to study applied decisions to understand whether these basic principles also apply to decisions people make every day and how the knowledge on basic decision making can be used to improve decisions in applied contexts. One such context is the medical domain, in which patients must choose between medical treatments, each with certain probabilities of improving a medical condition and of causing side effects. Because these probabilities are usually known through clinical trials, patients in those situations face a decision under risk, but with medical outcomes instead of money or points. In comparison to monetary lotteries, in medical decisions people generally seem to make choices as if they neglect or strongly distort probabilities (Pachur et al., 2014; Popovic et al., 2019; Suter et al., 2016).

Despite these and other consistent behavioral patterns people demonstrate in decisions under risk, choices can be volatile to the features of the decision maker and the environment. On the one hand, people's stable traits such as cognitive abilities (Cokely et al., 2018; Peters, 2020) and their fluctuating states such as mood (e.g., Fehr-Duda et al., 2011; Traczyk & Fulawka, 2016) can influence how people deal with decisions under risk. On the other hand, the structure of the environment plays a crucial role in risky choice. For instance, choices depend on the way people learn about information or on defaults (e.g., Ritov & Baron, 1990; Wulff et al., 2018). Because risky choices seem to be influenced by states of the decision maker and the structure of the environment, it has been argued that preferences in risky choices are not clear and stable, but are rather constructed "on-the-spot" (Lichtenstein & Slovic, 2006; Payne et al., 1999). This dissertation aims to provide further insights into how the environment shapes preference construction in decisions under risk in the basic domain and an applied domain. Whereas in Research Papers 1 and 2, we use monetary lotteries to study the basic processing of information, in Research Paper 3, we study decisions under risk in the medical domain.

1.1.2 The Role of the Environment

Despite their differences, diverse perspectives on human decision making agree that the environment plays a crucial role in how people make decisions (Lichtenstein & Slovic, 2006; Payne et al., 1993; Todd et al., 2012; Tversky & Kahneman, 1981). This is in line with empirical findings showing that choices depend, among other things, on the way people learn about information (e.g., Hertwig, 2015), time constraints (e.g., Payne et al., 1996), defaults (e.g., Ritov & Baron, 1990), whether choosing for oneself or someone else (e.g., Polman & Wu, 2019), the domain (e.g., medical vs. monetary; Pachur et al., 2014), or the addition of a seemingly irrelevant options (e.g., Hadar et al., 2018). The current dissertation aims to provide further insights into the role of the environment in decisions under risk by focusing on the way people learn about information as well as time constraints.

Past research has consistently shown that the way people learn about information influences how they deal with the outcome and probabilities and thus make choices. For instance, people seem to treat the same probabilities differently when they are explicitly described vs. when people have to learn about them through sequential sampling (Hertwig et al., 2004; Wulff et al., 2018) or when probabilities are presented numerically vs. graphically (e.g., Trevena et al., 2021). However, previous research on the effects of the *learning mode* (or *presentation format*) on decisions has almost exclusively studied decision making between options which are represented in the same way and has varied learning modes only between conditions. Thereby, it has neglected the role of the learning mode of the alternative option(s) when making decisions under risk. Understanding how the learning mode of the alternative option influences the evaluation of an option not only helps to better understand how robust the effects of the learning mode are, but also reveal insights into the role of the choice context in decision making. To study how the consistency of representation between the available options affects decisions under risk in a basic and an applied context, Research Papers 1 and 3 systematically vary the learning mode of the alternative options and study how people process and evaluate information about options.

Further, time constraints have an impact on how accurately, fast, and consistently people choose (e.g., Olschweski & Rieskamp, 2021; Payne et al., 1996). However, little is known about how well people trade off the benefits and costs of time in risky choice when there are opportunity costs of time. Further, it is unclear how time pressure affects the processing of numerically, graphically, and inconsistently represented information.

Extending the knowledge on how time constraints affect decision making is not only important to understand how people treat time in decisions, but can also enable conclusions about the investment of cognitive effort when making decisions. Therefore, Research Papers 2 and 3 study the role of time constraints in decisions under risk.

1.1.3 Information Processing in Risky Choice

Although in decisions under risk, choices are arguably the most relevant outcome, choice data by itself provides limited insight into the processes underlying these choices. Whereas a careful selection of choice problems and a sophisticated study design may allow to distinguish choice strategies (e.g., Glöckner & Herbold, 2011) or examine the treatment of probabilities (e.g., Hertwig et al., 2004), the conclusions about information processing are limited when studying choices only. However, studying response times and using choice data for computational modeling can provide deeper insights into choice processes.

The time people spend deliberating before making a choice does not only allow for a more fine-grained examination of decision making, but can also enable insights into choice processes. For instance, response times allow to draw conclusions about invested cognitive effort (e.g., Payne et al., 1996) or help to discriminate between choice strategies (e.g., Pachur, 2021). Research Papers 2 and 3 go beyond choice data and examine response time as a valuable source of information about how people process information in decisions under risk.

Data on choices and response times, however, can reveal deeper insights into the processing of information if they are used to develop and test computational models which describe and predict choice behavior (Busemeyer & Diederich, 2009; Farrell & Lewandowsky, 2018; Wang & Busemeyer, 2021). Although different people may ultimately choose the same option, computational modeling allows to capture differences in the processing and evaluation of risky options. Research Papers 1 and 2 take advantage of the strengths and benefits of computational modeling and use both choice and response-time data to draw conclusions about subjective representation of information and information processing in decisions under risk.

1.1.4 The Present Dissertation

The present dissertation aims to study information processing in decisions under risk and how it depends on the structure of the environment. By studying decisions in both a basic setting and an applied context, by considering various features of the environment, and by both examining behavioral data and conducting computational modeling, this dissertation takes a comprehensive approach to studying decisions under risk. As a whole, the three following research papers extend the existing knowledge on human decision making, raise important questions for future research, and can serve as a foundation to improve decisions for people across a wide range of domains.

1.2 Research Paper 1: The Role of Choice Context in Risky Choice

Information about options' outcomes and their probabilities can differ in how it is provided to the decision maker by the environment. For example, the weather forecast states the likelihood of precipitation as a number, whereas the probability of having a nice dinner at a certain restaurant has to be based on one's own or others' experiences. Previous research has consistently shown that the way people learn about information affects the evaluation of those options (Wulff et al., 2018). However, it is unclear to what extent the evaluation of one option is affected by the learning mode of the *alternative* option. How does the context of the choice (i.e., the learning mode of the alternative option) affect subjective representations of the outcomes and probabilities of both options? In Research Paper 1, my co-authors and I use computational modeling to study the role of choice context in search and choice behavior in decisions under risk.

1.2.1 Summary of Research Paper 1: Choosing between Described and Experienced Risky Options: No Gap, but a Similar Evaluation of Options

In decisions under risk, preferences are not only a function of the available options, but also of the structure of the environment. One intensively studied feature of the environment is the *learning mod*e, that is, the way people learn about possible outcomes of each option and their probabilities: outcomes and probabilities are either described explicitly in summary form (*decisions from description*; e.g., weather forecasts); or they have to be learned from sequential experiences with the options (*decisions from experience*; e.g., crossing the road). Research has shown that the evaluation of options seems to be influenced by differences in the learning mode (e.g., Hertwig et al., 2004; Wulff et al., 2018). For instance, people subjectively represent outcome and probability information differently in decisions from description than in decisions from experience (e.g., Glöckner et al., 2016; Kellen et al., 2016).

To date, research on this *description–experience gap* has primarily focused on comparing situations in which all options are described with situations in which all options are experienced (e.g., Hertwig et al., 2004; Wulff et al., 2018). For that reason, these studies have not been designed to systematically investigate the role of the learning mode of the alternative option. If the learning mode of an option affects only its own evaluation irrespective of the choice environment, people should evaluate an option in the same way regardless of whether the alternative option is described or experienced. Consequently, when choosing between a described and an experienced option, the evaluations and thus the subjective representations of outcomes and probabilities would differ between options. If, however, evaluations depend on the choice context, differences in the learning mode of the alternative option should affect subjective representations. The goal of the present research is to test this possibility: Do subjective representations of probability and outcome information differ when the learning mode of the options differs within a choice problem—that is, when one option is described and the other is experienced? Or are both options in choice situations with mixed learning modes integrated into a common representation and, if so, how does this representation compare with situations in which all options are described or experienced?

Furthermore, this research aims to test whether people would exhibit a preference for a specific learning mode in the mixed condition. Given the evidence for ambiguity aversion (Ellsberg, 1961; Trautmann & van de Kuilen, 2015), it seems likely that people may display a systematic preference for the precise described option over the more ambiguous experienced option. However, it is also possible that people show a preference for the experienced option, given that people have to actively sample from it and thus may pay more attention to it and people tend to choose the option they spent more time looking at (Krajbich & Rangel, 2011; Krajbich et al., 2010).

Finally, the research aims also to investigate the role of choice context in information search. In particular, we test if the number of samples drawn from an experienced option is affected by whether it is paired with another experienced option or a described option. We hypothesize that people draw more samples per option in a mixed condition than in a purely experience-based condition in an attempt to align the certainty about the experienced option to that of the described option. Additionally and more exploratorily, we examine how search effort for the experienced option is influenced by the properties of the described option in choices with mixed learning modes.

In an experiment, 218 participants made 112 choices between two risky options. The study's three conditions differed in terms of how participants learned about the outcome distributions of the options presented at each trial. In the *description* condition, outcomes and their probabilities were presented in summary format and in the *experience* condition, participants could draw samples from the options' payoff distributions. In the *mixed* condition, one option was presented as in the description condition and the other as in the experience condition.

To measure and compare participants' subjective representation of outcome and probability information, we modeled the choice data using cumulative prospect theory (CPT; Tversky & Kahneman, 1992). To test whether subjective representations of outcomes and probabilities differed within a choice in the mixed condition, we used a variant of CPT with separate parameter sets per option. In case there were no differences, we would follow the standard CPT approach which assumes same parameter sets for both options.

Replicating findings on differences between description- and experience-based choices (Glöckner et al., 2016; Kellen et al., 2016), we found that the shapes of CPT's value and weighting functions differed between the purely description-based and purely experience-based conditions. In the mixed condition, however, there was no evidence that the value and weighting functions for the described and experienced options differed. The parameters estimated for outcome sensitivity, probability sensitivity, and choice sensitivity in the mixed condition fell between those estimated for the pure description and experience conditions. Thus, our results suggest a joint subjective representation of outcomes and probabilities for both learning modes which reflects a compromise between pure description and pure experience.

Further, there was no evidence for a bias toward either of the learning modes in the mixed condition. Finally, people sampled more information per option when comparing the experienced option with a described option than with a second experienced option. The sample size in the mixed condition, in turn, was affected by properties of both the experienced option and the described option and by the absolute value difference between the options.

In conclusion, we show that decision making between options in different learning modes differs systematically from decision making between options in the same learning mode. More generally, our findings highlight the role of choice context and, specifically, the reciprocal influence of options and their respective learning mode when people construct preferences in risky choice.

1.3 Research Paper 2:
The Trade-Off between the Costs and Benefits of Time

The environment may not only vary in how it provides information, but also how much time it provides to deliberate and how valuable that time is. When deliberation time is costly, people have to trade off the costs of time and its benefits (i.e., higher accuracy). The most efficient trade-off, in turn, depends on the price of time and the differences between the values of the options. In Research Paper 2, my co-authors and I study how well people perform this trade-off in risky choice and how adaptively people adjust their information processing to the level of opportunity costs and the differences in options' values.

1.3.1 Summary of Research Paper 2: Good Time, Bad Time: Do People Invest Processing Effort Adaptively in Decision Making with Opportunity Costs?

When making decisions, time often matters. Time spent making one decision could be invested in making another, or payoffs become less available or attractive over time. On the other hand, time also can improve a decision, as longer deliberation can lead to more accurate processing of the options; this investment, however, only pays off if the options actually differ sufficiently in value. Decision makers thus have to trade off the benefits of further deliberating against the costs of time, taking into account the options' differences in value. Whereas investigations on risky choice often treat time as free—and thus ignore this important trade-off between the costs and benefits of time—some investigations have shown that people make faster and less accurate choices when there are *opportunity costs of time* (Hausfeld & Resnjanskij, 2018; Payne et al., 1996; Rieskamp & Hoffrage, 2008). It is currently unclear, however, how adaptively this response to opportunity costs is and how well people trade off the costs and benefits of time in decisions under risk.

We address this issue using the drift diffusion model (DDM; Ratcliff, 1978; Ratcliff & McKoon 2008) as a computational framework. The DDM is a sequential sampling model according to which information about options is accumulated over time until an evidence boundary is reached. There is a boundary for each option, and the distance between the boundaries is assumed to capture the decision maker's conservatism. The DDM can thus implement a speed-accuracy trade-off, with wider boundaries leading to slower but more accurate choices.

When there are opportunity costs of time and thus every unit of time leads to a certain loss in payoff, there exists a boundary separation which trades off the costs and benefits of time most efficiently and maximizes expected payoff. Based on simulations, we first determined how people should adapt their boundary separation in order to maximize payoffs depending on the level of opportunity costs and on the differences in options' value.

Next, we examined whether people adjust their boundary separations adaptively in line with the simulations by conducting three empirical experiments. In all experiments, participants made multiple choices between two risky options. As in the simulations, the level of opportunity costs and difference in option value (i.e., expected value) were manipulated across conditions. In the opportunity-costs conditions, all outcome values decreased by a certain number of points every 750ms. In the no-opportunity-costs condition, outcomes remained fixed.

In Experiment 1 (N = 271), we manipulated between participants the opportunity costs on three levels (no, low, and high costs) and the differences in option value on three levels (large, moderate, small). In Experiment 2 (N = 90), we manipulated value differences within participants to allow each participant to experience different degrees of value differences. In Experiment 3 (N = 92), we tested if participants would be more sensitive to differences in value when adaptivity is higher rewarded (i.e., when option values differed by a large amount) and how participants would treat negligible opportunity costs. For that purpose, we repeated Experiment 2 with different factor levels (opportunity costs: no costs vs. negligible vs. high; differences in option value: low vs. high vs. very high). In all three studies, we modeled people's choices with the DDM and determined the optimal boundary separation for each condition (cf. Starns & Ratcliff, 2012).

Across all experiments, people's estimated boundary separation (as measured with the DDM) differed considerably as a function of whether there were opportunity costs or not, but there was relatively little modulation between different levels of opportunity costs. Further, in contrast to the implications of the simulation, estimated boundary separations were only limitedly sensitive to value differences. In particular, boundary separations were somewhat sensitive to value differences when adaptivity was rewarded highly (i.e., given large differences between values), but not when differences were smaller than that. As a result of the limited sensitivity, estimated boundaries were narrower than optimal when value differences were large and wider than optimal when value differences were small. Furthermore, although the simulation suggested guessing (i.e., boundary separation close to 0) to be optimal in choice problems with similarly attractive options, participants did not adopt this strategy.

Taken together, we demonstrate how adaptive decision making trading off costs and benefits of processing time can be studied within a computational framework. Our empirical results suggest that people have only limited abilities to adaptively adjust their information processing during decision making with different levels of opportunity costs. Importantly, they show only little sensitivity to or knowledge about how differences in option value affect how much time they should invest into a decision.

1.4 Research Paper 3: The Role of Cognitive Effort in Processing Medical Information

The way people learn about information and time constraints also play a role when patients need to make a decision between medical treatments. On the one hand, physicians and other providers can choose how to present the benefits and risks of treatments. On the other hand, the time available to choose an option may differ across medical conditions, patients, and situations. Both the presentation format and available time can potentially influence how people process medical information and thus make treatment choices. In Research Paper 3, my co-author and I study how the presentation format and time constraints affect information processing and choices in decisions under risk in an applied medical context.

1.4.1 Summary of Research Paper 3: Graphical Representations of Medical Information Require More Cognitive Effort than Numbers, but are Preferred

In order to make informed medical decisions, patients have to understand the benefits and risks associated with the medical treatments available, which is often challenging. Various studies have demonstrated that people understand medical information better when it is presented using graphical formats such as icon arrays than using numbers (Trevena et al., 2021). However, less attention has been paid to the cognitive processes underlying the effect of presentation format, in particular how easily people process graphical and numerical formats.

The first goal of this study is to investigate how much cognitive effort processing graphically and numerically represented information requires by examining the time people spend deliberating as an indicator of cognitive effort (McCaffery et al., 2012; Oudhoff & Timmermans, 2015; Zikmund-Fisher et al., 2010). Previous research has shown that people take more time to respond to questions when they work with graphical formats than with numbers (Garcia-Retamero et al., 2016; Smerecnik et al., 2010; but see Brewer et al., 2012). However, the correlational design of these studies could not test whether participants took more time to deliberate or they rather needed more time to process the information. Our study aims to disentangle these accounts by experimentally studying comprehension of information when time is limited. If one format requires higher cognitive effort than another, it should not only lead to longer response times, but also to worse decisions and understanding of information when there is time pressure.

The second goal is to study how people process inconsistently represented information, that is when information is presented partly numerically and partly graphically. We study whether processing inconsistently represented information requires more cognitive effort and leads to worse decisions and understanding than with fully numerical or graphical representations. We further test whether when being provided with inconsistently represented information, people translate the information of one representation into another before comparing options and whether prompting people to perform this translation improves decisions. Moreover, we test whether formats can bias treatment preferences in inconsistent representation.

Finally, the third goal of this study is to investigate whether numerical abilities (i.e., numeracy; Peters, 2012, 2020) and graphical abilities (i.e., graph literacy; Galesic & Garcia-Retamero, 2011) are not only associated with a better understanding of numerical and graphical information, but also a more efficient processing thereof.

To study processing of medical information, we conducted a preregistered experiment (N = 665). Participants were provided with information on the relative frequencies of benefits and side effects of six hypothetical medications and were asked questions about them. The medical information was constructed so that there were two dominant, superior treatments. The way the information was presented differed between conditions. In the *numerical* conditions, frequencies were presented as numbers and in the *graphical* conditions, frequencies were presented as icon arrays. In the *inconsistent* conditions, information on three medications was presented numerically, whereas the information on the other three medications was presented as icon arrays. Further, we manipulated between participants whether there was time pressure. In the *time-pressure* conditions, participants had to answer each question within a time limit but there was no time limit in the *no-time-pressure* conditions. In an additional *intervention* condition, participants were provided with inconsistent information but were asked to translate the graphical into numerical information before answering the questions. All participants were asked to choose the medication they would prefer as a patient and to answer knowledge questions about the medications. Finally, numeracy and graph literacy were assessed.

The results showed that when information was presented graphically (vs. numerically), people took longer to answer the knowledge questions and the knowledge scores were more strongly harmed by time pressure. However, for decisions there was no difference in response times or accuracy. These findings suggest that graphical formats require more cognitive effort than numerical formats when knowledge is important, but not necessarily when comparing information in decisions.

When information was presented inconsistently, people took longer to respond than with numbers only. Further, in the inconsistent conditions, decision accuracy and knowledge were lower than in the numerical conditions and knowledge scores were even lower when there was time pressure. When comparing the inconsistent condition with the graphical condition, results were mixed: Decisions were made slower in the inconsistent condition, but answers to knowledge questions were given faster. Decisions in the inconsistent condition were less accurate than in the graphical condition, but there was no significant difference between conditions for knowledge. Participants in the intervention condition performed well when translating graphical into numerical information and had higher decision accuracy and knowledge when their translations were presented when answering questions than without. Moreover, in the inconsistent condition, participants exhibited a preference for the graphically represented medications. These findings suggest that integrating inconsistently presented information poses a considerable cognitive burden and people seem to be able to translate information from one representation into another, but do not do so if not explicitly asked for. Further, the format in which medications are presented do not only seem to affect understanding, but also to bias preferences.

Finally, knowledge of people higher in numeracy was less harmed than that of people lower in numeracy, suggesting that higher (vs. lower) numeracy also enables people to process information more efficiently.

In conclusion, our findings show that not only the understanding of medical information differs between numerical and graphical formats, but also how people process them. More generally, our findings emphasize the value of studying the processing of medical communication beyond the examination of outcome measures and highlight the importance of considering features of the environment as well the goals of risk communication when studying risk formats.

1.5 General Discussion

The goal of this dissertation is to provide further insights into the role of the environment in information processing in decisions under risk. The three research papers of this dissertation focus on the way people learn about information and on time constraints as two features of the environment and study information processing in decisions under risk in the basic and in an applied domain. In Research Paper 1, we found that the context of the choice (i.e., the learning mode of the alternative option) affected subjective representations of outcome and probability information of an option as well as search effort. In Research Paper 2, we showed that people seem to have limited abilities to adaptively adjust their information processing to differences in options' values and the level of opportunity costs. In Research Paper 3, we found that processing icon arrays requires mores cognitive effort than processing numbers and processing inconsistently represented information results in worse understanding and decisions than the processing of consistently representation information. Together, these findings emphasize the significant impact of the structure of the environment on decisions and help to better understand how decisions are shaped by the environment.

A plethora of previous research has demonstrated that the processing, understanding, and evaluation of information depends on the way we learn about it (e.g., McDowell & Jacobs, 2017; Trevena et al., 2021; Wulff et al., 2018). However, this research almost exclusively focused on situations in which all available information is represented in the same way. Therefore, it did not systematically investigate the influence the learning mode of the alternative option(s) could have on the evaluation of an option and how people integrate information which is provided in different ways. This dissertation fills this gap by studying decisions under risk when the information about options is presented in the same learning mode (or presentation format) or in different ones. In two research papers, we study how people subjectively represent information and how much cognitive effort they have to invest depending on the consistency of the learning mode (or presentation format) across options. Our findings show that subjective representation of one option depends on whether the learning mode of the alternative option is the same or a different one and that inconsistently represented information requires more cognitive effort than when all available information is presented in the same presentation format. Therefore, our research suggests that the effect of learning mode (or presentation format) on information processing and choices may be less robust than often suggested (e.g., Wulff et al., 2018), but may rather depend on features of the choice context.

Furthermore, time plays a crucial role in most decisions, either because it is limited or a valuable good. However, most research on decisions under risk give people unlimited time to search for information and make a decision, thus neglecting how people treat time in decision making. The current dissertation studies the role of time in decisions and how time constraints influence the processing of information and the following decisions. In two research papers, we could show that taking time constraints into account when studying decisions reveals new insights into information processing in decisions under risk. In particular, studying decisions with opportunity costs of time revealed that people only have a limited ability to adjust their information processing to features of the choice problem and the environment. Further, the implementation of time limits allowed us to show that the processing of one representation format requires more cognitive effort than the processing of another format. Thus, our research shows that studying the effects of time constraints on decisions does not only extend the knowledge on the role of the environment in decision making under risk, but can also help to better understand information processing in these decisions.

Whereas monetary lotteries are a useful tool to study the basic processes underlying human decision making, studying medical decision making can help to aid patients to make informed choices about treatments. Whereas in the basic and the applied domain, people make choices between risky options, decision making in the two domains is mostly studied separately (but see e.g., Pachur et al., 2014). This dissertation shows the value of bringing them together. Studying basic information processing in medical decisions can help to understand how and why presentation formats affect understanding and provides knowledge for developing decisions aids in order to improve patient decision making. On the other hand, basic research on decision making can benefit from incorporating ecologically more valid paradigms such as inconsistent information representation. With this dissertation, I hope to encourage further research which brings together different domains harnessing each other’s strengths.

The research of this dissertation introduces new avenues for future research. First, our findings invite future research to study information integration from different learning modes. We could show that people subjectively represent a described and an experienced option jointly when choosing between them, but more research is needed to understand which processes underlie the integration of inconsistently provided information. Further, studying how attention is allocated when choosing between differently represented options could provide another approach to better understand the role of the learning mode in decision making. Second, despite the ubiquity of opportunity costs of time in everyday decision making, relatively little previous research has focused on how people treat time in decision making. How do people process time and its costs when making decisions? How do people differ in the trade-off between the costs and benefits of time? How can the trade-off between the costs and benefits of time be improved? Our research provided important insights into how people treat time in decision making with opportunity costs, yet it raised a range of new questions for future research. Third, in order to help patients understand medical information, it can be helpful to tailor the information to not only the decision maker (Gaissmaier et al., 2012), but also to the situation in which patients make their decision. Our research suggests that considering the available cognitive and time resources could aid information providers to present information in a way that best helps patients to make informed decisions. Future research on risk communication should further investigate how the understanding of information presented in different formats depends on features of the environment.

Together, the three research papers of this dissertation not only provide important insights into how the environment shapes information processing in risky choice by implementing novel research paradigms. They also demonstrate that decisions are heavily impacted by the environment they are made in. Thus, they emphasize the importance of considering the structure of the environment in order to understand human decision making and its underlying processes. Moreover, understanding how decisions depend on the environmental structure can also help to adapt the environment and educate people in a way that improves the decisions people face every day.

References

Brewer, N. T., Gilkey, M. B., Lillie, S. E., Hesse, B. W. & Sheridan, S. L. (2012). Tables or bar graphs? Presenting test results in electronic medical records. *Medical Decision Making, 32*(4), 545–553. https://doi.org/10.1177/0272989X12441395

Busemeyer, J. R., & Diederich, A. (2009). *Cognitive modeling*. SAGE.

Cokely, E. T., Feltz, A., Ghazal, S., Allan, J. N., Petrova, D., & Garcia-Retamero, R. (2018). Skilled decision theory: From intelligence to numeracy and expertise. In K. A. Ericsson, R. R. Hoffman, A. Kozbelt, & A. M. Williams (Eds.), *The Cambridge handbook of expertise and expert performance* (pp. 476–505). Cambridge University Press.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, *75*(4), 643–669. https://doi.org/10.2307/1884324

Farrell, S., & Lewandowsky, S. (2018). *Computational modeling of cognition and behavior*. Cambridge University Press.

Fehr-Duda, H., Epper, T., Bruhin, A., & Schubert, R. (2011). Risk and rationality: the effects of mood and decision rules on probability weighting. Journal of Economic Behavior & Organization, 78(1–2), 14–24. https://doi.org/10.1016/j.jebo.2010.12.004.

Fox, C. R., Erner, C., & Walters, D. J. (2015). Decision under risk: From the field to the laboratory and back. In G. Keren & G. Wu (Eds.), *The Wiley Blackwell handbook of judgment and decision making* (Vol. 1, pp. 43–88). Wiley-Blackwell.

Gaissmaier, W., Wegwarth, O., Skopec, D., Müller, A.-S., Broschinski, S., & Politi, M. C. (2012). Numbers can be worth a thousand pictures: Individual differences in understanding graphical and numerical representations of health-related information. *Health Psychology*, *31*, 286–296. https://doi.org/10.1037/a0024850

Galesic, M., & Garcia-Retamero, R. (2011). Graph literacy: A cross-cultural comparison. *Medical Decision Making*, *31*, 444–457. https://doi.org/10.1177/0272989X10373805

Garcia-Retamero, R., Cokely, E. T., Wicki, B., & Joeris, A. (2016). Improving risk literacy in surgeons. *Patient Education and Counseling*, *99*(7), 1156–1161. https://doi.org/10.1016/j.pec.2016.01.013

Glöckner, A., & Herbold, A. An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making*, *24*, 71–98. https://doi.org/10.1002/bdm.684

Glöckner, A., Hilbig, B. E., Henninger, F., & Fiedler, S. (2016). The reversed description–experience gap: Disentangling sources of presentation format effects in risky choice. *Journal of Experimental Psychology: General*, *145*(4), 486–508. https://doi.org/10.1037/a0040103

Goldstein, W. M., & Weber, E. U. (1997). Content and discontent: Indications and implications of domain specificity in preferential decision making. In W. M. Goldstein & R. M. Hogarth (Eds.), *Research on judgment and decision making: Currents, connections, and controversies* (pp. 566–617). Cambridge University Press.

Hadar, L., Danziger, S., & Hertwig, R. (2018). The attraction effect in experience-based decisions. *Journal of Behavioral Decision Making, 31*(4), 461–468. https://doi.org/10.1002/bdm.2058

Hausfeld, J., & Resnjanskij, S. (2018). *Risky decisions and the opportunity cost of time* (Working Paper No. 269). ifo Institute. Munich.

Hertwig, R. (2015). Decisions from experience. In G. Keren & G. Wu (Eds.), *The Wiley Blackwell handbook of judgment and decision making* (Vol. 1, pp. 240–267). Wiley-Blackwell.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–292. https://doi.org/10.2307/1914185

Kellen, D., Pachur, T., & Hertwig, R. (2016). How (in)variant are subjective representations of described and experienced risk and rewards? *Cognition*, *157*, 126–138. https://doi.org/10.1016/j.cognition.2016.08.020

Knight, F. (1921). *Risk, uncertainty, and profit*. Houghton-Mifflin.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(33), 13852–13857. https://doi.org/10.1073/pnas.1101328108

Lichtenstein, S., & Slovic, P. (2006). *The construction of preference*. Cambridge University Press.

Lopes, L. L. (1983). Some thoughts on the psychological concept of risk. *Journal of Experimental Psychology: Human Perception and Performance, 9*(1), 137–144. https://doi.org/10.1037/0096-1523.9.1.137

McCaffery, K. J., Dixon, A., Hayen, A., Jansen, J., Smith, S., & Simpson, J. M. (2012). The influence of graphic display format on the interpretations of quantitative risk information among adults with lower education and literacy: A randomized experimental study. *Medical Decision Making*, *32*(4), 532–544. https://doi.org/10.1177/0272989X11424926

McDowell, M., & Jacobs, P. (2017). Meta-analysis of the effect of natural frequencies on Bayesian reasoning. *Psychological Bulletin*, *143*(12), 1273–1312. https://doi.org/10.1037/bul0000126

Olscheski, S., & Rieskamp, J. (2021). Distinguishing three effects of time pressure on risk taking: Choice consistency, risk preference, and strategy selection. *Journal of Behavioral Decision Making*. Advance online publication. https://doi.org/10.1002/bdm.2228

Oudhoff, J. P., & Timmermans, D. R. M. (2015). The effect of different graphical and numerical likelihood formats on perception of likelihood and choice. *Medical Decision Making*, *35*(4), 487–500. https://doi.org/10.1177/0272989X15576487

Pachur, T. (2021). How information integration costs shape strategy selection in decision making: A Bayesian multimethod approach. In A. Huckauf, M. Baumann, M. Ernst, C. Herbert, M. Kiefer, & M. Sauter (Eds.), *Contributions to the 63rd Tagung Experimentell arbeitender Psychologen* (pp. 186–187). Pabst Science Publishers.

Pachur, T., Hertwig, R., & Wolkewitz, R. (2014). The affect gap in risky choice: Affect-rich outcomes attenuate attention to probability information. *Decision, 1*(1), 64–78. https://doi.org/10.1037/dec0000006

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.

Payne, J. W., Bettman, J. R., & Luce, M. F. (1996). When time is money: Decision behavior under opportunity-cost time pressure. *Organizational Behavior and Human Decision Processes*, *66*(2), 131–152. https://doi.org/10.1006/obhd.1996.0044

Payne, J. W., Bettman, J. R., & Schkade, D. A. (1999). Measuring constructed preferences: Towards a building code. *Journal of Risk and Uncertainty*, *19*, 243–270. https://doi.org/10.1023/A:1007843931054

Peters, E. (2012). Beyond comprehension: The role of numeracy in judgments and decisions. *Current Directions in Psychological Science*, *21*(1), 31–35. https://doi.org/10.1177/0963721411429960

Peters, E. (2020). *Innumeracy in the wild: Misunderstanding and misusing numbers*. Oxford University Press.

Polman, E., & Wu, K. (2020). Decision making for others involving risk: A review and meta-analysis. *Journal of Economic Psychology*, *77*, 102184, https://doi.org/10.1016/j.joep.2019.06.007

Popovic, N. F., Pachur, T., & Gaissmaier, W. (2019). The gap between medical and monetary choices under risk persists in decisions for others. *Journal of Behavioral Decision Making, 32*(4), 388–402. https://doi.org/10.1002/bdm.2121

Ratcliff, R. (1978). A theory of memory retrieval. Psychological Review, 85(2), 59–108. https://doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, *20*(4), 873–922. https://doi.org/10.1162/neco.2008.12-06-420

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. https://doi.org/10.1016/j.actpsy.2007.05.004

Ritov, I., & Baron, J. (1990). Reluctance to vaccinate: Omission bias and ambiguity. *Journal of Behavioral Decision Making*, *3*(4), 263–277. https://doi.org/10.1002/bdm.3960030404

Smerecnik, C. M. R., Mesters, I., Kessels, L. T. E., Ruiter, R. A. C., de Vries, N. K., & de Vries, H. (2010). Understanding the positive effects of graphical risk information on comprehension: Measuring attention directed to written, tabular, and graphical risk information. *Risk Analysis*, *30*(9), 1387–1398. https://doi.org/10.1111/j.1539-6924.2010.01435.x

Starns, J. J., & Ratcliff, R. (2012). Age-related differences in diffusion model boundary optimality with both trial-limited and time-limited tasks. *Psychonomic Bulletin & Review*, *19*(1), 139–145. https://doi.org/10.3758/s13423-011-0189-3

Suter, R. S., Pachur, T., & Hertwig, R. (2016). How affect shapes risky choice: Distorted probability weighting versus probability neglect. *Journal of Behavioral Decision Making*, *29*(4), 437–449. https://doi.org/10.1002/bdm.1888

Todd, P. M., & Gigerenzer, G. (Eds.). (2012). *Ecological rationality: Intelligence in the world.* Oxford University Press.

Traczyk, J., & Fulawka, K. (2016). Numeracy moderates the influence of task-irrelevant affect on probability weighting. *Cognition*, *151*, 37–41. http://doi.org/10.1016/j.cognition.2016.03.002

Trautmann, S. T., and van de Kuilen, G. (2015). Ambiguity Attitudes. In G. Keren & G. Wu (Eds.), *The Wiley Blackwell handbook of judgment and decision making* (Vol. 1, pp. 89–116). Wiley-Blackwell.

Trevena, L. J., Bonner, C., Okan, Y., Peters, E., Gaissmaier, W., Han, P. K. J., Ozanne, E., Timmermans, D., & Zikmund-Fisher, B. J. (2021). Current challenges when using numbers in patient decision aids: Advanced concepts. *Medical Decision Making*, *41*(7), 834–847. https://doi.org/10.1177/0272989X21996342

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453–458. https://doi.org/10.1126/science.7455683

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574

Wang, Z. J., & Busemeyer, J. R. (2021). *Cognitive choice modeling*. The MIT Press.

Wulff, D. U., Mergenthaler-Canseco, M., & Hertwig, R. (2018). A meta-analytic review of two modes of learning and the description-experience gap. *Psychological Bulletin*, *144*(2), 140–176. https://doi.org/10.1037/bul0000115

Zikmund-Fisher, B. J., Fagerlin, A., & Ubel, P. A. (2010). A demonstration of “less can be more” in risk graphics. *Medical Decision Making*, *30*(6), 661–670. https://doi.org/10.1177/0272989X10364244

Chapter 2:
The Role of Choice Context in Risky Choice

Choosing between Described and Experienced Risky Options: No Gap, but a Similar Evaluation of Options

Kevin E. Tiede[1,2], Wolfgang Gaissmaier[2,3], & Thorsten Pachur[4]

[1]Graduate School of Decision Sciences, University of Konstanz
[2]Department of Psychology, University of Konstanz
[3]Centre for the Advanced Study of Collective Behaviour, University of Konstanz
[4]Center for Adaptive Rationality, Max Planck Institute for Human Development

Funding was provided by the Graduate School of Decision Sciences, University of Konstanz, Germany. We thank Alisa Auer and Lisa-Marie Walther for their help with data collection and Susannah Goss for editing the manuscript.

Abstract

People choosing between risky options seem to evaluate the options differently depending on whether they learn about them from a summary description (*decisions from description*) or from drawing sequential samples from the payoff distribution (*decisions from experience*). However, little is known about how the evaluation of an option in one learning mode is affected by the choice context, specifically the learning mode of the alternative option. When choosing between a described and an experienced option, are options evaluated differently within a choice or rather jointly? We compared people's choice and search behavior in such a mixed condition with their behavior in a purely description- or experience-based condition. Using cumulative prospect theory (CPT) to model choices and map people's subjective representations of outcome and probability information, we found clear differences between the purely description-based and the purely experience-based conditions. In the mixed condition, however, the subjective representations of the described and the experienced options were similar, and the shapes of CPT's value and weighting functions fell between those for the other two conditions, suggesting that people formed a joint representation of options. Participants did not demonstrate any preference for a specific learning mode. Finally, per-option search effort in the mixed condition was higher than in the purely experience-based condition and was sensitive to the expected value and the variance of the described option. These findings highlight the role of choice context and, specifically, the reciprocal influence of options and their respective learning mode when people construct preferences in risky choice.

2.1 Introduction

In decisions under risk, preferences are not only a function of the individual, but also of the structure of the environment. Thus, it has been argued that preferences in risky choice are, at least to some degree, constructed (Johnson et al., 2005; Lichtenstein & Slovic, 2006; Payne et al., 1999). One feature of the environment which has been studied intensively is the *learning mode*, that is, the way people learn about the possible outcomes of each option and their probabilities: outcomes and probabilities are either described explicitly in summary form (*decisions from description;* e.g., weather forecasts); or they have to be learned from sequential experiences with the options (*decisions from experience;* e.g., crossing the road). Research has shown that people's preferences seem to be influenced by differences in the learning mode (e.g., Hertwig et al., 2004; Wulff et al., 2018). For instance, the weight rare events (e.g., side effects of medications) seem to receive differs in *decisions from description* from in *decisions from experience*.

To date, research on the *description–experience gap* has primarily focused on comparing situations in which all options are described with situations in which all options are experienced (e.g., Hertwig et al., 2004; Wulff et al., 2018). Because usually the learning mode is varied for both options simultaneously, these studies are not designed to systematically investigate the role of the choice context in risky choice, in this case the learning mode of the alternative option. If the learning mode of an option affects only its own evaluation irrespective of the choice environment, people should evaluate a described option in the same way regardless of whether the alternative option is described or experienced. Consequently, when choosing between a described and an experienced option, the weighting of probabilities would differ and thus a description–experience gap within a choice would emerge. If, however, preferences depend on the choice context, differences in the learning mode of the alternative option should affect the evaluation. In line with that proposition, previous research has shown that processes of judgment and preference are influenced by the extent to which options can be structurally aligned (Hsee, 1996; Lichtenstein & Slovic, 1971; Tversky et al., 1988; see also Markman & Gentner, 1993). This alignability is inevitably reduced when options require different learning modes. Consequently, differences in how a described versus an experienced option is evaluated may be affected by the choice context, in particular whether that option is compared with an option in the same or a different learning mode.

The goal of the present article is to test this possibility: Do subjective representations of probability and outcome information differ when the learning mode of the options differs *within* a choice problem—that is, when one option is described and the other is experienced? Or are both options in choice situations with mixed learning modes integrated into a common representation and, if so, how does this representation compare with situations in which all options are described or experienced? We use computational modeling with cumulative prospect theory (CPT; Tversky & Kahneman, 1992) to model choices and to map people's subjective representations of outcomes and probabilities in these choices. In addition, we investigate how people search for information about an experienced option when they have to evaluate it against a described option, thus providing insights into how search and choice behavior depends on the context of the choice (i.e., the learning mode of the other option). In so doing, we seek to determine whether learning from description or experience generally gives rise to different types of evaluation, or whether the differences observed are also driven by the context in which the information is presented.

In the following, we summarize previous findings on the differences between description- and experience-based choices and outline possible forms that the subjective representation of outcome and probability information might take in choices between a described and an experienced option. We then report an experiment that compares subjective representations and search behavior in this mixed condition with behavior in purely description- or experience-based conditions. Our results demonstrate that both the subjective representation of outcomes and probabilities (indicating, for instance, how a risky outcome is weighted) as well as the search effort for an experienced option depend strongly on whether it is presented in a choice problem that offers another experienced option or a described option.

2.1.1 Decisions from Description Versus Experience

Empirical research on decision making under risk often employs paradigms involving monetary outcomes and the probabilities of these outcomes. The most frequently used approach is to ask people to choose between two lotteries with explicitly described outcomes and probabilities—for example, between "10% to win $10; 90% to win $0" and "$1 for sure". These descriptions resemble those that people encounter in weather forecasts or medication package inserts.

In everyday life, however, probabilities are rarely explicitly stated. Rather, people have to estimate them based on their own or others' experiences. When choosing a restaurant, one cannot consult a chart that specifies the probability of being served a good meal. Rather, one has to estimate that probability based on the outcomes of one's own or others' previous restaurant visits. A common method to study such experience-based decision making is the *sampling paradigm* (Hertwig et al., 2004; Hertwig & Erev, 2009). Here, the decision maker can learn about the payoff distributions of the available options (i.e., the outcomes and their probabilities) by drawing individual samples. For instance, someone drawing 10 samples from the risky option above might see "0,0,0,0,0,0,0,10,0,0," while 10 samples from the sure option will show "1,1,1,1,1,1,1,1,1,1." In the sampling paradigm, people can usually draw as many samples as they want.

In most studies comparing description-based and experience-based decision making, participants are asked to choose between two described or two experienced options, and choice behavior is then compared between these conditions. These studies have consistently found differences in choice patterns between these two learning modes (for a meta-analysis, see Wulff et al., 2018). One important driver of these differences is that people making decisions from experience draw relatively small samples (median = 10 per option; Wulff et al., 2018), and due to sampling error the information they sample from the options can divert from the options' "objective" characteristics (see also Fox & Hadar, 2006). For instance, some people drawing 10 samples from the lottery above ("10% to win $10; 90% to win $0") will not draw the $10 outcome at all; others will draw it twice or more. But sampling error does not seem to be the only factor contributing to differences between description- and experience-based choices.

Several investigations using cumulative prospect theory (CPT) to model people's choices have found that their subjective representations of experienced outcomes and experienced probabilities (defined as the relative frequency with which the outcomes were sampled) differ from their subjective representations when this information is described (e.g., Abdellaoui et al., 2011; Glöckner et al., 2016; Kellen et al., 2016; Ungemach et al., 2009). In brief, CPT assumes that the outcomes of an option are transformed non-linearly into subjective values (a formal description of CPT is provided in Section 2.2.4). The more strongly curved the function, the less sensitive a decision maker is to differences in outcomes. In addition, loss outcomes receive more psychological weight than do gains of the same size (loss aversion). CPT further assumes that the outcomes are weighted by decision weights, which follow from a non-linear transformation of the objective probabilities based on a probability weighting function. The curvature of this function indexes the decision maker's sensitivity to probability information, with a more pronounced curvature indicating lower sensitivity. Glöckner et al. (2016) and Kellen et al. (2016) found that people are less sensitive to differences in probabilities and more sensitive to differences in outcomes in experience- than in description-based choices.

As noted above, most previous research on the effect of experience on people's decisions has focused on situations in which the information for all options is either described *or* experienced. A few studies have also considered the interplay of description and experience, such as when additional samples can be drawn from options for which a description is available. For instance, in a study by Weiss-Cohen et al. (2016), participants were provided with a described summary of the options, but they could additionally draw samples from the options. In one condition, the described information matched the experienced information; in another, it differed. In a third condition, participants made purely experience-based choices. When the described and experienced information was matched, participants' tendency to choose the risky option was similar to that observed for purely experience-based choices, suggesting that the described information was neglected. When the described and experienced information was in conflict, however, choice behavior differed from that observed in the experience and the matched-information conditions, indicating that the described information was also taken into account. Computational modeling showed that when the described and experienced information was in conflict, people took both types of information into account, but the described information seemed to receive less weight. Other studies have shown that the influence of description is moderated not only by whether described and experienced information match, but also by the plausibility of the described information, the complexity of the task, and the timing of experiencing the information (Lejarraga & Gonzalez, 2011; Weiss-Cohen et al., 2016, 2018, 2021).

But what about situations in which the options require different learning modes? Might there also be differences *within* a choice problem, such that the subjective representations of the described and experienced options differ? If there were differences between description and experience between choices, but not within a single choice, this would suggest that subjective representations of outcomes and probabilities are driven not only by the payoff distribution and the learning mode of the option itself but also by the context in which the choice is made, namely by the learning mode of the other option. And finally, how do people search for information when they choose between options in different learning modes?

To our knowledge, only one previous study has examined decisions in choice problems where participants learned about options through different learning modes. In Ert and Trautmann (2014, Study 1), one option was described explicitly (e.g., "You receive 2 shekels with probability 0.2; otherwise nothing") and participants sampled the outcomes from another option (with the same payoff distribution). It emerged that the higher the probability of winning the reward was, the more likely participants were to choose the experienced option, suggesting that information is treated differently depending on how it is learned. However, because the information actually experienced was not taken into account in the analysis, these differences could also be due to sampling error (i.e., due to the experienced payoff distributions deviating from the described ones). In particular, the choice pattern indicated that rare outcomes received less weight than their objective, underlying probabilities would warrant, which is in line with rare outcomes being sampled less often when samples sizes are small. In addition, the analysis was mute with respect to the subjective representations of individual options in terms of CPT parameters. Therefore, it is not possible to draw conclusions about differences between learning modes within a choice.

In the present study, we examine sensitivity to differences in outcomes and probabilities, making it possible to test whether options in the mixed condition are treated differently depending on the learning mode and, if not, how the subjective representation relates to that in description- and experience-based choices. In addition, we investigate how people search for information when they choose between options in different learning modes.

2.1.2 Choice and Search Behavior in Choices Between a Described and an Experienced Option

2.1.2.1 Do Subjective Representations of Outcome and Probability Information Differ Between Options in a Mixed Condition?

As noted above, people's choices suggest that they represent outcomes and probabilities differently when making decisions from description versus experience (e.g., Glöckner et al., 2016; Kellen et al., 2016). Do such differences in subjective representation also emerge when a described and an experienced option are paired within a choice problem?

If so, in a *separate-representations* scenario, people may show lower sensitivity to differences in probability and higher sensitivity to outcomes in the experienced option than in the described option (Glöckner et al., 2016; Kellen et al., 2016).

Alternatively, people may evaluate both options on the basis of a joint subjective representation. In a *joint-as-description* scenario, the subjective representations of probabilities and outcomes could resemble those observed in purely description-based choices. Consistent with that possibility, a study by Fox et al. (2013) showed that experience-based choices could be made more like description-based ones by prompting participants to “repack” the sampled outcomes: Participants were asked to draw colored cards but were only told the assignment of colors to outcome values after completing the sampling process. They were thus required to recall the probabilities of the cards in order to evaluate the options and make their choices. In this condition, the level of risk seeking was similar to that observed in description-based choices, but differed from that observed in experience-based choices and a fourth condition in which the color assignment was presented before sampling.

Analogously, a *joint-as-experience* scenario is in principle conceivable, in which the subjective representations of probabilities and outcomes resemble those observed in purely experience-based choices.

It is also possible that the described and the experienced options are evaluated on the basis of a joint representation that differs qualitatively from that of purely description- or experience-based choices—for instance, if relative comparisons are made between the options. In this case, people could try to make the options more comparable by converging the representations of the two learning modes. In this *joint-compromise* scenario, they could shift the representation of each learning mode in the direction of the other, so that the subjective representations of outcomes and probabilities would reflect a compromise between those observed in purely description- or experience-based choices.

Finally, also a *joint-shifted* scenario is conceivable, if it plays a role how easily the two options can be compared or aligned. Hsee (1996; Hsee et al., 1999) has shown that people give more weight to attributes that can be evaluated more easily. Arguably, it will be easier to evaluate an attribute value that can be compared with another value in the same learning mode. In the mixed condition, outcome information is easily compared, whereas the format of probability information differs between the described and the experienced options. Thus, probability sensitivity may be similar for both options in the mixed condition, but lower than in problems where both options are presented in the same learning mode.

In the present study, we first tested whether subjective representations of outcomes and probabilities differed between described and experienced options in the mixed condition and, if not, then determined how they compared to those in purely description- and experience-based choices.

2.1.2.2 Do Differences in Learning Mode Bias Choice?

In a choice problem offering both a described and an experience option, choices may also be influenced by the differences between the options with regard to the certainty of the information. Whereas with a described learning mode probabilities are provided as explicit, error-free information, in an experienced learning mode the probabilities can only be estimated from the sampled outcomes; the information is thus more ambiguous. Given the evidence for ambiguity aversion (Ellsberg, 1961; Trautmann & van de Kuilen, 2015), people may display a systematic preference for the described option over the more ambiguous experienced option. Also in support of this possibility, Lejarraga (2010) found that people who were able to choose whether to make decisions on the basis of description or experience preferred description.

However, it is also possible that people show a preference for the experienced option, given that people have to actively sample from it and thus may pay more attention to it. Because people tend to choose the option they spent more time looking at (Krajbich & Rangel, 2011; Krajbich et al., 2010), this could lead to a systematic preference for the experienced option (but see Ert and Trauman, 2014, who found no evidence that a particular learning mode was preferred).

To test these possibilities, we examined whether there was a bias towards choosing the described or the experienced option, controlling for the subjective valuations of the options.

2.1.2.3 How Much Information Do People Search for in the Mixed Condition?

An attractive feature of the sampling paradigm is that it makes it possible to examine information search in decisions from experience. Research has shown that when both options in a choice problem are experienced, people tend to draw relatively small samples. In the present study, we investigated whether the number of samples drawn from an experienced option is affected by whether it is paired with another experienced option or with a described option. It seems reasonable to hypothesize that people draw more samples per option in a mixed condition than in a purely experienced condition in an attempt to align the certainty about the experienced option to that of the described option. In addition, sampling incurs opportunity costs (i.e., time; Hertwig & Pleskac, 2010). If all sampling efforts can be invested in one option, people may draw more samples from that option than when sampling efforts have to be distributed across two options.

As an additional and more exploratory research question, we examined how search effort for the experienced option is influenced by the properties of the described option in choices with mixed learning modes. Research on experience-based choices has shown that people sample more in the loss domain than in the gain domain, when the variance of the options is larger, and when the differences in expected value (EV) between the options are smaller (Lejarraga et al., 2012; Mehlhorn et al., 2014; Pachur & Scheibehenne, 2012; Wulff et al., 2018). By the same token, when an experienced option is paired with a described option, the number of samples taken from the experienced option might be affected by, for example, the number of outcomes or the variance of the described option. We therefore examined how people's sampling behavior is affected by the properties of the described and the experienced option separately. In sum, by studying how search effort for an experienced option is affected by the learning mode and the properties of the other option, we hope to gain insights into how choice and information search are affected by the context of the choice.

2.1.3 The Present Study

This study addressed three main questions. First, do people's subjective representations of outcome and probability information (as measured within CPT) differ between the described and experienced options in a mixed condition, and thus reflect differences in evaluation between learning modes? If not, how does the joint subjective representation in the mixed condition relate to that in a purely description- or experience-based condition? Second, do people have a preference for one of the learning modes? Third, how much search effort do people invest in the mixed condition relative to a purely experience-based condition? Prior to the study reported below, we conducted a pilot study with a very similar design but different choice problems and an online participant sample. The results (which were very similar to those reported here) are reported in the Supplemental Materials (Section S1.1).

2.2 Methods

2.2.1 Participants

Participants were students from the University of Konstanz, Germany (mostly undergraduates), who participated in return for either €10.00 (equivalent to about $11.14 at the time of the study) or course credit. In addition, all participants received a performance-contingent bonus of M = €1.17 (SD = 0.53; see below for details). Data were collected from 229 participants. We excluded seven participants who did not choose the dominant option in at least three out of four attention check trials and four participants who did not sample any outcomes in at least a quarter of the trials, indicating low levels of engagement in the task. The final sample (N = 218) comprised 167 women, 48 men, and 3 people who identified as gender diverse, with a mean age of M = 22.8 years (18–45; SD = 4.1).

2.2.2 Decision Task

In the decision task, participants made 112 choices between two monetary lotteries. The study's three conditions (see Figure 2.1 for screenshots) differed in terms of how participants learned about the payoff distributions of the two options presented at each trial. In the *description* condition, outcomes and their probabilities (as percentages) were presented in summary format. In the *experience* condition, participants could draw samples from the options' payoff distributions by pressing a "play lottery" button. Each time the button was pressed, one outcome of the distribution was drawn randomly (based on its probability); participants were free to sample as many outcomes as they wanted from each option before making a final choice by pressing the respective "choose lottery" button. In the *mixed* condition, one option (chosen randomly) was presented as in the description condition and the other as in the experience condition. In this condition, the side (left vs. right) of the described option was randomized across participants but kept constant across the experiment. The left/right ordering of the options and, in the description condition, the order of outcomes within an option were randomized on the trial level for all participants and conditions. We used choice problems that have been shown to allow for accurate estimation of CPT parameters in previous studies (e.g., Glöckner & Pachur, 2012; Kellen et al., 2016; see Broomell & Bhatia, 2014): We included 81 randomly generated choice problems covering the gain, loss, and mixed domains (Rieskamp, 2008), as well as six problems constructed to measure risk aversion (Holt & Laury, 2002) and 10 problems constructed to measure loss aversion (Gächter et

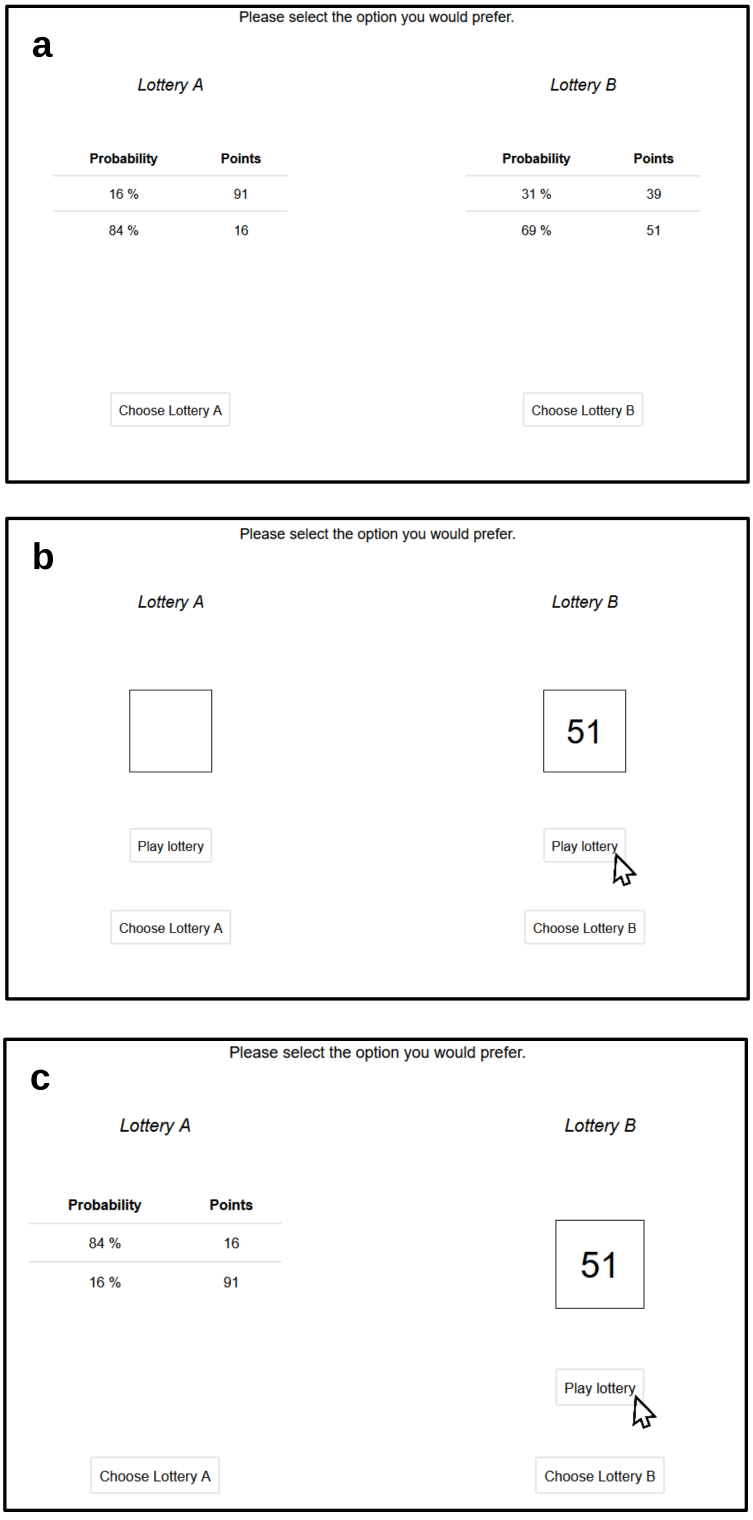

Figure 2.1: Screenshots of trials in the (a) description, (b) experience, and (c) mixed condition (translated from the original German).

al., 2007). In addition, we included the six choice problems used in the original study on the description–experience gap (Hertwig et al., 2004) and the five problems used by Ert and Trautmann (2014) in their study (i.e., choices between the same options). Finally, four choice problems with one stochastically dominant option were included as an attention check, given a total of 112 problems. All choice options had one or two outcomes, which ranged from −100 to 100 (some problems were scaled to this range). A table listing all choice problems used in this study can be found in the Supplemental Materials (Section S1.2).

2.2.3 Procedure

After providing informed consent, participants were randomly assigned to one of the three conditions. They were informed that one of the choice problems would be randomly chosen and played to determine their bonus, with the points earned being converted to cents and added to a starting amount of €1.00. Following instructions and a questionnaire tapping subjective numeracy (i.e., preference for numbers and numeric confidence; see Section Supplemental Materials, Section S1.3, for details), participants completed two practice trials and the main task. They then completed an unrelated task not reported here that took, on average, 4.3 minutes (*SD* = 1.6). Finally, participants answered a questionnaire tapping objective numeracy (i.e., the ability to use probabilistic and mathematical concepts; see Supplemental Materials, Section S1.3, for details), were informed about their bonus, and were debriefed.

2.2.4 Computational Modeling

To measure and compare participants' subjective representation of outcome and probability information, we modeled the choice data using CPT (Tversky & Kahneman, 1992). CPT is based on the assumption that decision makers choose as if they non-linearly transform objective outcomes and probabilities into subjective values and decision weights, respectively, which determine the subjective valuation of each option. The option with the highest subjective valuation V is chosen. For an option with outcomes $x_1 \leq \ldots \leq x_k \leq 0 \leq x_{k+1} \leq \ldots \leq x_n$ and corresponding probabilities $p_1 \ldots p_n$, the subjective valuation V is defined as:

$$V = \sum_{i=1}^{k} \pi_i^- v(x_i) + \sum_{j=k+1}^{n} \pi_j^+ v(x_j) \quad , \tag{1}$$

with v as a value function satisfying $v(0) = 0$, and π^+ and π^- as decision weights for gains and losses, respectively. In other words, V is the sum of all subjective values v assigned to each outcome weighted by the respective decision weights.

The value function describes the non-linear transformation of an objective outcome into a subjective value and is defined as

$$\begin{aligned} v(x) &= x^{\alpha} && \text{if } x \geq 0 \\ v(x) &= -\lambda(-x)^{\alpha} && \text{if } x < 0, \end{aligned} \tag{2}$$

where outcome sensitivity parameter α reflects the sensitivity to differences in outcomes and captures the curvature of the value function.[2] If $\alpha < 1$, the value function has a concave curvature for gains and a convex curvature for losses, reflecting decreasing sensitivity to differences in outcomes with increasing outcome magnitude. If $\alpha > 1$, sensitivity to differences in outcomes increases with outcome magnitude. The parameter λ indicates loss aversion and captures how much worse a loss is perceived to be relative to a gain of the same magnitude. When $\lambda > 1$, the value function is steeper for losses than for gains.

Furthermore, CPT assumes that the transformation of objective probabilities into subjective decision weights depends on the rank of the outcome with which the probability is associated. The resulting decision weights are defined as:

$$\begin{aligned} \pi_1^- &= w^-(p_1) \\ \pi_n^+ &= w^+(p_n) \\ \pi_i^- &= w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) && \text{for } 1 < i \leq k \\ \pi_j^+ &= w^+(p_j + \cdots + p_n) - w^+(p_{j+1} + \cdots + p_n) && \text{for } k < j < n, \end{aligned} \tag{3}$$

with w^+ and w^- being the probability weighting functions for gains and losses, respectively. In other words, the decision weight π^+ (π^-) given to a positive (negative) outcome is the difference between the weight—as defined by the weighting functions—based on the probability of receiving an outcome as good (bad) as or better (worse) than x and the weight based on the probability of receiving an outcome better (worse) than x.

The weighting function w describes the transformation of probabilities:

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}} \ . \tag{4}$$

[2] Note that whereas separate outcome sensitivity and probability sensitivity parameters have often been estimated for gains and losses in applications of CPT (e.g., Tversky & Kahneman, 1992), subsequent research has shown that this approach can lead to distortions in parameter estimation (Nilsson et al., 2011, 2020). We therefore estimated a common α and γ for both gains and losses.

The probability sensitivity parameter γ governs the weighting function's curvature and indicates the sensitivity to probability differences. Values of $\gamma < 1$ lead to an inverse S-shaped weighting function and reflect overweighting of small probabilities and underweighting of moderate-to-large probabilities. The smaller $\gamma < 1$ becomes, the stronger the curvature of the function and the more overweighted small probabilities become. Values of $\gamma > 1$ reflect underweighting of small probabilities.

We used two variants of CPT in order to test whether subjective representations of outcomes and probabilities differed within a choice problem in the mixed condition and if not, to compare the joint subjective representations to that in a purely description- or experience-based condition. In the joint-representation CPT model, parameter values were constrained to be the same for both options. In the separate-representations CPT model, separate parameter sets were estimated for the described option (i.e., α_d, λ_d, and γ_d) and the experienced option (i.e., α_e, λ_e, and γ_e) in the mixed condition. Results indicating there were no differences between these two parameter sets would suggest that both options are represented similarly. In that case, we would follow the standard joint-representation CPT approach and assume same parameter sets for both options for the mixed condition.

To derive a predicted choice probability, we used the probabilistic choice rule softmax (see Stott, 2006), which defines the probability of the option with the higher valuation V (i.e., Option A) being chosen as

$$p\ (A, B) = \frac{e^{\varphi V(A)}}{e^{\varphi V(A)} + e^{\varphi V(B)}}\ , \tag{5}$$

where V(A) and V(B) are the subjective valuations of Option A and B, respectively. The parameter $\varphi > 0$ reflects the sensitivity to differences in valuations. When $\varphi = 0$, choices are random. With higher values of φ, the probability of choosing the option with the higher valuation approaches 1, making choices more deterministic.

To test the extent to which participants had a general preference for one of the learning modes, we also tested a variant of that choice rule which allows such a bias to be captured using an additive constant (e.g., Walasek & Stewart, 2015). The choice rule variant is defined as:

$$p(D, E) = \frac{e^{\varphi V(D)+\beta}}{e^{\varphi V(D)+\beta} + e^{\varphi V(E)}}\ , \tag{6}$$

where β is a bias parameter that captures a tendency to choose the described option (D) over the experienced option (E) irrespective of the subjective valuation of the options.

When $\beta = 0$, there is no bias. With values of $\beta > 0$, the probability of choosing the described option over the experienced option increases beyond the subjective valuations: there is a bias towards the described option. Values of $\beta < 0$ indicate a bias towards the experienced option. We first used this choice rule for the mixed condition, to test whether there was a bias towards either the described or the experienced option. If this was not the case, and β did not differ from 0, we would proceed with the standard choice rule (Eq. 5).

We used a hierarchical Bayesian approach (Nilsson et al., 2011; Scheibehenne & Pachur, 2015) to estimate the CPT parameters. In Bayesian parameter estimation, parameters are initially represented in terms of prior distributions that are then updated to posterior distributions based on the observed data (for an introduction, see Lee & Wagenmakers, 2013). Hierarchical Bayesian modeling represents a compromise between modeling the data of each participant individually and modeling the aggregated data for a group of participants. Whereas the latter ignores individual differences and can thus lead to distorted results (Estes & Maddox, 2005), the former can result in noisy and unreliable estimates, especially if there are only few data points available per participant (Scheibehenne & Pachur, 2015). In the hierarchical approach, the individual parameters are assumed to be drawn from a group-level distribution that is simultaneously estimated. Hierarchical Bayesian modeling has been shown to yield more reliable and accurate estimates than does modeling individual data (Kruschke & Vanpaemel, 2015; Nilsson et al., 2011; Scheibehenne & Pachur, 2015).

We estimated the individual-level and group-level posterior distributions for all CPT parameters using JAGS 4.3.0 and the R package R2jags (Su & Yajima, 2020). We ran three chains, each with 310,000 samples and with a burn-in period of 10,000 samples. To reduce autocorrelation, we thinned the chains such that every 50th sample was recorded, resulting in 6,000 recorded samples per chain. We assessed chain convergence using the potential scale reduction factor $\hat{R}$ (Gelman & Rubin, 1992). For most estimated parameters, $\hat{R}$ was smaller than 1.01 (for all, $\hat{R} < 1.042$), indicating overall good convergence (Brooks & Gelman, 1998).

2.3 Results

The attention check trials and choices between the same options were excluded from the analyses, which thus covered a total of 103 choice problems. Trials in which no outcomes were drawn from at least one option were excluded from the analysis (0.6% of trials). The data and analysis scripts for the pilot and main study are available at https://osf.io/2ym3f/?view_only=eeae4e98328f4757a78dbf90aa0e5a42.

2.3.1 Do Subjective Representations of Outcomes and Probabilities Differ Between the Described and Experienced Option?

For the CPT parameter estimates, we report means of the group posterior distribution and the respective 95% highest density intervals (95% HDI). The 95% HDI contains 95% of the distribution such that parameter values outside the interval have lower probability than parameter values inside the interval. The group-level parameters were linked with the individual level (assuming normal distributions on both levels) through probit transformations (see Rouder & Lu, 2005; Scheibehenne & Pachur, 2015). Two parameter values are considered credibly different when the 95% HDI of the differences between distributions does not include 0. As a measure of model performance, we report the Deviance Information Criterion (DIC), which takes into account model complexity; lower values reflect better model performance. A difference in DIC of more than 10 is considered to indicate that one model performs reliably better than the other (see Spiegelhalter et al., 2002, p. 613).

2.3.1.1 Differences between Description and Experience Conditions

First, we tested whether we could replicate previous findings of differences in the subjective representation of outcomes and probabilities (as implied by CPT's value and weighting functions) between the purely description-based and the purely experience-based conditions. To this end, we estimated CPT parameters in both conditions. The parameter estimates are reported in Table 2.1; the value and probability weighting functions are plotted in Figure 2.2. In the experience condition, outcome sensitivity α was higher, probability sensitivity γ was lower, loss aversion λ was higher, and choice sensitivity φ was lower than in the description condition. These results replicate findings by Glöckner et al. (2016) and Kellen et al. (2016) on differences in sensitivity to outcomes and probabilities between description- and experience-based choices—and extend these findings to the extent that we found differences in all CPT parameters.

2.3.1.2. Subjective Representations of Outcomes and Probabilities in the Mixed Condition

Next, we tested whether differences in the subjective representations of outcomes and probabilities were also observed in the mixed condition, where one option is described and the other is experienced. To this end, we estimated a CPT model with separate sets of parameters for the described and the experienced option. The means of the estimated group-level posterior distributions are reported in Table 2.2. It emerged that the estimated values for the described and the experienced option did not differ credibly from each other for any of the parameters (i.e., the 95% HDI of the difference between the two

Table 2.1: Posterior group-level Mean parameters of the CPT model [95% HDI].

Parameter	Description condition (n = 73)	Experience condition (n = 78)	Mixed condition (n = 67)	Difference Descr. – Exp.	Difference Mixed – Descr.	Difference Mixed – Exp.
Outcome sensitivity α	0.80 [0.76–0.84]	1.13 [1.07–1.19]	1.02 [0.97–1.07]	**−0.33 [−0.40–−0.27]**	**0.22 [0.16–0.28]**	**−0.11 [−0.18–−0.03]**
Probability sensitivity γ	0.81 [0.74–0.87]	0.62 [0.58–0.66]	0.72 [0.67–0.78]	**0.19 [0.11–0.26]**	**−0.09 [−0.17–0.00]**	**0.10 [0.04–0.17]**
Loss aversion λ	1.20 [1.07–1.32]	1.55 [1.31–1.79]	1.28 [1.14–1.42]	**-0.35 [−0.62–−0.08]**	0.08 [−0.10–0.28]	−0.26 [−0.55–0.01]
Choice sensitivity φ	0.21 [0.17–0.26]	0.04 [0.03–0.06]	0.08 [0.06–0.10]	**0.17 [0.13–0.21]**	**−0.13 [−0.19–−0.09]**	**0.03 [0.01–0.06]**

Note. Descr. = Description condition, Exp. = Experience condition, Mixed = Mixed condition. Credible differences are printed in boldface.

Table 2.2: Posterior group-level mean parameters of the CPT model with separate parameters for each option in the mixed condition [95% HDI].

Parameter	Described option	Experienced option	Difference described – experienced
Outcome sensitivity α	1.02 [0.98–1.07]	1.03 [0.98–1.07]	−0.01 [−0.01–0.00]
Probability sensitivity γ	0.74 [0.68–0.81]	0.68 [0.64–0.72]	0.06 [0.00–0.14]
Loss aversion λ	1.26 [1.17–1.35]	1.28 [1.19–1.37]	−0.02 [−0.07–0.02]
Choice sensitivity φ	0.08 [0.06–0.09]		

options did not include zero). To further corroborate this finding, we conducted a model comparison (based on DIC) with a CPT model that assumed the same parameter for the described and the experienced option. The DIC of this simpler model was lower (indicating better model performance) than that allowing for differences between the described and the experienced option, DIC = 7553.9 vs. 7622.6. We thus conclude that the subjective representations of the described versus experienced outcome and probability information did not differ in the mixed condition.

2.3.1.3. Comparing the Mixed Condition with the Other Conditions.

Because the CPT parameters did not differ across the described and the experienced options in the mixed condition, we applied the CPT model with identical parameters across options for all conditions and compared the parameter values in the mixed condition with those in the description and experience condition. The estimated model parameters are reported in Table 2.1 and plotted in Figure 2.2. For all parameters, the mean of the group-level posterior distribution in the mixed condition fell between that of the description and the experience condition. With regard to the outcome sensitivity parameter α, the probability sensitivity parameter γ, and the choice sensitivity parameter φ, the values in the mixed condition differed credibly from both description and experience condition. In contrast, the value of the loss aversion parameter λ in the mixed condition was not credibly different from that in either the description or the experience condition.

Taken together, the results suggest that participants relied on a joint representation of both options rather than on separate representations. This joint representation represented a compromise between description- and experience-based choices, reflecting the joint-compromise scenario.

2.3.2 Is There a Choice Bias in the Mixed Condition?

We further tested whether participants had a systematic preference for a specific learning mode. To that end, we modeled choices in the mixed condition using a variant of the choice rule that included an additive parameter β reflecting a bias towards one of the options, irrespective of its subjective evaluation. A positive (negative) value indicates a bias towards the described (experienced) option. We estimated the parameter using the CPT model with same parameters for both options, which showed the best model performance in the analysis above. With this model, β was positive but did not credibly differ from 0 (group-level posterior mean = 0.07 [−0.02–0.15]). We thus conclude that participants did not show a credible bias towards the described or the experienced option in general.

2.3.3 How Do People Search for Information in the Mixed Condition?

Next, we examined sampling behavior in the mixed condition and the experience condition. We hypothesized that participants might draw a larger number of samples per

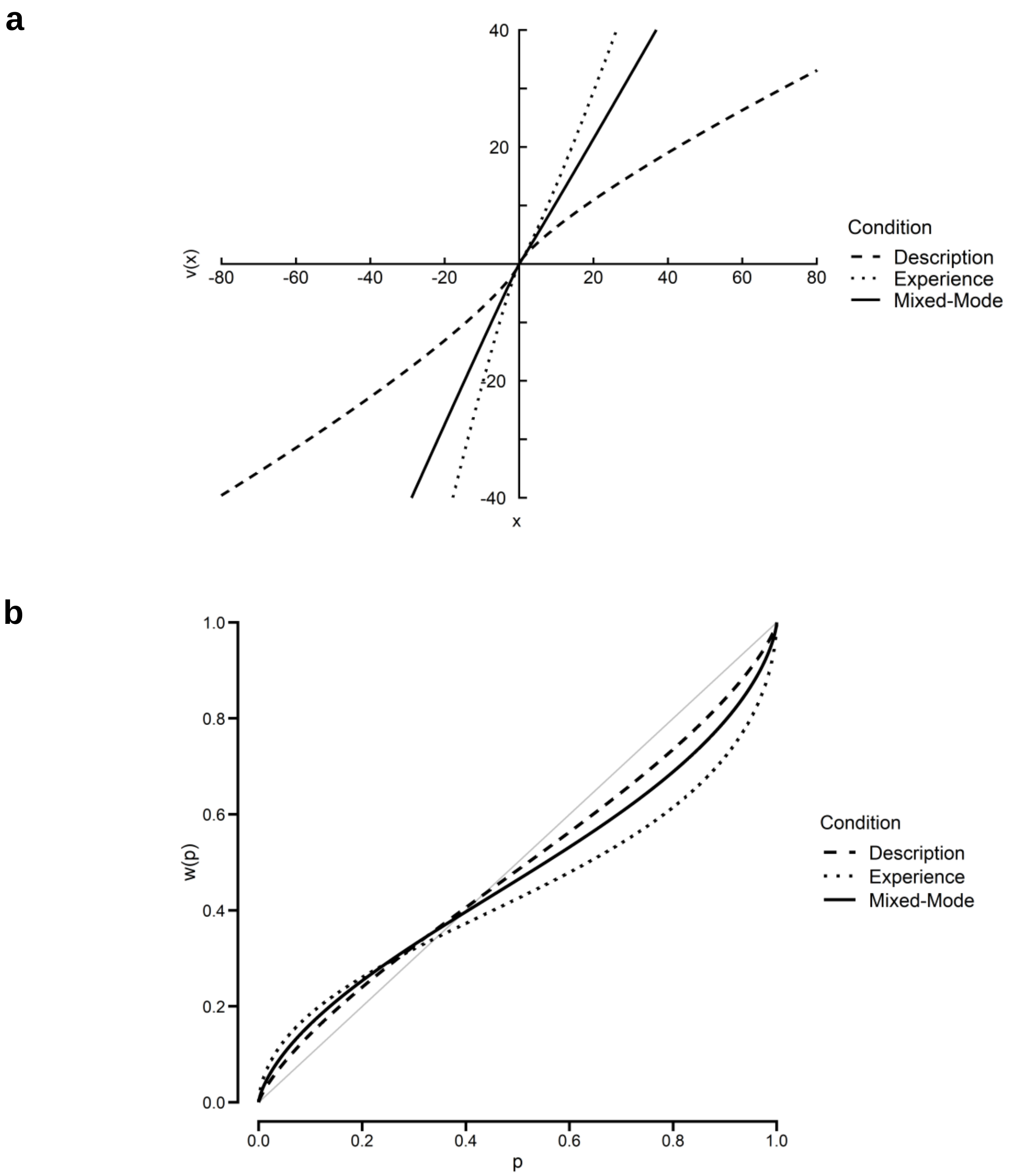

Figure 2.2: Posterior group-level mean (a) value functions and (b) probability weighting functions for the description, experience, and mixed conditions.

option in the mixed condition than in the purely experience-based condition in an attempt to align the level of certainty of the two options. Indeed, our results showed that in the mixed condition the mean number of samples drawn from the experienced option was larger than the mean number of per-option samples in the experience condition (M_{mixed} = 22.5, SD_{mixed} = 12.0 vs. $M_{\text{experience}}$ = 16.4, $SD_{\text{experience}}$ = 8.1; $t(112.45) = 3.50$, $p < .001$).

We also explored how search effort in the mixed condition was influenced by features of the choice problems and by properties of both the experienced and the described option. To this end, we conducted a multilevel analysis with random effects for participants. For each option, we included the following properties as predictor variables based on the actually experienced information: expected value (EV), number of outcomes, standard deviation (SD), SD normalized by the EV (i.e., coefficient of variation, CV; Weber et al., 2004). Further, we included the absolute difference between the two options in terms of EV, SD, and CV. The dependent variable was sample size. The results are reported in Table 2.3. The number of samples drawn was higher when the described option had a lower EV and a higher SD, but was not influenced by the number of outcomes or the CV of the described option. The only property of the experienced option that affected sample size was EV, with a higher number of samples being drawn when the experienced option had a higher EV. Further, sample size was higher with smaller absolute difference in EV and SD. In an additional analysis, we analyzed the choice problems in the gain and loss domain only and included domain as a predictor (see Lejarraga et al., 2012); domain did not affect sample size (b = 0.35, SE = 1.10, p = .752).

Next, we tested whether the EV and SD of the alternative option affected search effort in an experienced option only when the alternative option was described or whether this was an effect of the alternative option per se. To this end, we examined search effort in the experience condition for each option individually, thus disentangling the influence of the properties of an experienced option from those of its alternative on search effort. Full results are reported in the Supplemental Materials (Section S1.3). Our results showed that choice context also affected search effort in the experience condition. Specifically, the effects of the properties of the alternative option were similar to those observed in the mixed condition (where the other option was described): EV was negatively and SD positively associated with sample size, whereas number of outcomes and CV did not influence sample size. However, the effects of properties of the target

Table 2.3: Effect of properties of the choice problem on the size of the sample drawn for the experienced option in the mixed condition.

Predictor	*b*	*SE*	*p*
Intercept	23.34	1.68	< .001
DO: EV	**−0.05**	**0.01**	**< .001**
EO: EV	**0.02**	**0.01**	**.017**
DO: Number of outcomes	−0.48	0.74	.519
EO: Number of outcomes	0.69	0.57	.227
DO: SD	**0.05**	**0.01**	**< .001**
EO: SD	0.01	0.01	.262
DO: CV	−0.12	0.08	.165
EO: CV	−0.02	0.09	.834
Absolute EV difference	**−0.10**	**0.01**	**< .001**
Absolute SD difference	**−0.04**	**0.01**	**.002**
Absolute CV difference	0.01	0.09	.869

Note. DO = described option, EO = experienced option, EV = expected value, SD = standard deviation, CV = coefficient of variation. Significant predictors ($p < .05$) are printed in boldface.

option as well as differences between the options differed from those observed in the mixed condition. Also in contrast to the mixed condition, participants drew fewer samples in the loss than in the gain domain.

2.3.4 EV Maximization

Additionally, we examined how often participants chose the option with the higher EV—thus deciding in line with EV maximization—across the conditions. Full results are reported in the Supplemental Materials (Section S1.3). In short, participants chose the option with the higher EV similarly often in the experience condition and in the mixed condition. However, EV maximization was significantly lower in the description condition. This result replicates previous findings that description- and experience-based choices differ in terms of EV maximization (e.g., Wulff et al., 2018) and demonstrates that even having an experiential learning mode for just one option boosts EV maximization relative to purely description-based choices—despite the need to integrate information from different learning modes in the mixed condition.

2.3.5 The Role of Numeracy

Finally, we examined to what extent individual differences in objective numeracy (i.e., the ability to use probabilistic and mathematical concepts; Peters et al., 2006) and subjective numeracy (i.e., preference for numbers and numeric confidence; Fagerlin et al., 2007) were related to choice behavior in the mixed condition. Detailed results can be found in the Supplemental Materials (Section S1.3). Overall, there were no reliable associations. Objective and subjective numeracy were unrelated to sample size in the mixed or experience condition (although there was a positive association of objective numeracy and sample size in the pilot study). Further, there was no evidence that people with higher (vs. lower) objective numeracy were more consistently sensitive to probabilities across options in the mixed condition when CPT parameters were estimated separately for each condition. In sum, numeracy did not seem to have a substantial effect on choices and search effort in the mixed condition.

2.4 Discussion

When people make decisions under risk, they seem to evaluate the options differently depending on whether they learned about them through description or experience. Here, we studied the role of the choice context in risky choice and tested whether there are differences in evaluation of options when people choose between a described and an experienced option, using CPT to map people's subjective representations of outcomes and probabilities. Further, we tested whether choices in the mixed condition are biased toward one of the two learning modes. Finally, we examined to what extent information search depends on the properties of the options.

Replicating previous findings (Glöckner et al., 2016; Kellen et al., 2016), the shapes of CPT's value and weighting functions differed between the purely description-based and purely experience-based conditions. In the mixed condition, however, there was no evidence that the value and weighting functions for the described and experienced options differed, suggesting a joint subjective representation of outcomes and probabilities for both learning modes. The parameters estimated for outcome sensitivity, probability sensitivity, and choice sensitivity in the mixed condition fell between those estimated for the purely description and experience conditions. Thus, our results were in line with the proposed joint-compromise scenario that assumes a joint representation of both options. Further, there was no evidence for a bias toward either of the learning modes in the mixed condition. Finally, people sampled more information per option when comparing the experienced option with a described option than with a second experienced option. The sample size in the mixed condition, in turn, was affected by properties of both the experienced option and the described option and by the absolute value difference between the options.

Our results extend and qualify findings on differences between description- and experience-based choices. On the one hand, we replicated previous work showing that purely description-based choices seem to differ fundamentally from purely experience-based choices when patterns in choice are mapped using CPT. Although two previous studies have found differences in sensitivity to outcomes and probabilities (Glöckner et al., 2016; Kellen et al., 2016), this is the first study to find differences in all CPT parameters. Thus, our results suggest that differences between description and experience pertain not only to the weighting of probabilities, but that the mechanisms between the two learning modes differ more broadly. On the other hand, our findings indicate that differences between evaluations of a described and an experienced option cannot be attributed solely to the learning mode, but are also driven by the context in which the option is presented—specifically, whether it has to be compared with an option in the same or a different learning mode. This implies that the way the learning mode affects information processing and thus choices is to some extent context dependent, and thus underscores the constructed nature of risky choices (Lichtenstein & Slovic, 2006; Payne et al., 1999).

Our research thus emphasizes the role of context for choice and information search. Our results suggest that the subjective representation of an option depends heavily on the nature of the alternative option, particularly its learning mode. Participants' subjective representations of an option's outcome and probability information differed when it was compared to an option in the same versus a different learning mode. Interestingly, in choices between a described and an experienced option, the options affected each other's subjective representations reciprocally. This suggests that people do not tend to translate one learning mode into the other, but that they try to integrate the two options into a joint representation that reflects a compromise between purely description- and purely experience-based choices. In sum, our findings emphasize the importance of considering the choice context when developing choice models—as has indeed been done in promising models such as the Choice from Accumulated Samples of Experience (CHASE) model (Markant et al., 2015).

The choice context also affects search effort in experienced options. When the information about the alternative is precise and explicit, as in described options, people strive for higher reliability about the payoff distribution of the experienced option. By sampling more outcomes from that option, they align the levels of certainty of the two options. Moreover, search effort for an experienced option depends not only on the learning mode of the alternative option but also on its properties. In both the mixed and the experience condition, features of the alternative option affected how much information people searched for in an experienced option. This is, ceteris paribus, in line with predictions of the CHASE model (Markant et al., 2015), which models choices and sample sizes simultaneously. However, this model as well as previous examinations of sample size in experience-based choices (e.g., Wulff et al., 2018) have focused on how the properties of the choice problem affect sample size as a whole. By studying search effort in both options separately, we demonstrate that search effort depends on properties of both the option itself and its alternative, but that each option affects search effort differently. Our results thus indicate that more attention should be paid to choice context when studying choice and search behavior in decisions under risk.

2.5 Conclusion

Our research aimed to study the role of the choice context in risky choice, focusing on the learning mode of the alternative option. We found that decision making between options requiring different learning modes differs systematically from decision making between options in the same learning mode. Moreover, our findings highlight the role of choice context and, specifically, the reciprocal influence of options and their respective learning mode when people construct preferences in risky choice. In future research, it thus seems important to consider not only how people learned about an option, but also how they learned about the alternatives.

References

Abdellaoui, M., L'Haridon, O., & Paraschiv, C. (2011). Experienced vs. described uncertainty: Do we need two prospect theory specifications? *Management Science, 57*(10), 1879–1895. https://doi.org/10.1287/mnsc.1110.1368

Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, *7*(4), 434–455. https://doi.org/10.1080/10618600.1998.10474787

Broomell, S. B., & Bhatia, S. (2014). Parameter recovery for decision modeling using choice data. *Decision*, *1*(4), 252–274. https://doi.org/10.1037/dec0000020

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, *75*(4), 643–669. https://doi.org/10.2307/1884324

Ert, E., & Trautmann, S. T. (2014). Sampling experience reverses preferences for ambiguity. *Journal of Risk and Uncertainty*, *49*(1), 31–42. https://doi.org/10.1007/s11166-014-9197-9

Estes, W. K., & Maddox, W. T. (2005). Risks of drawing inferences about cognitive processes from model fits to individual versus average performance. *Psychonomic Bulletin & Review*, *12*(3), 403–408. https://doi.org/10.3758/BF03193784

Fagerlin, A., Zikmund-Fisher, B. J., Ubel, P. A., Jankovic, A., Derry, H. A., & Smith, D. M. (2007). Measuring numeracy without a math test: Development of the Subjective Numeracy Scale. *Medical Decision Making*, *27*(5), 672-680. https://doi.org/10.1177/0272989X07304449

Fox, C. R., & Hadar, L. (2006). “Decisions from experience” = sampling error + prospect theory: Reconsidering Hertwig, Barron, Weber & Erev (2004). *Judgment and Decision Making*, *1*(2), 159–161.

Fox, C. R., Long, A., Hadar, L., & Erner, C. (2013). *Unpacking decisions from description and experience* [Unpublished manuscript]. UCLA Anderson School of Management.

Gächter, S., Johnson, E. J., & Herrmann, A. (2007). *Individual-level loss aversion in riskless and risky choices* (IZA Discussion Paper No. 2961). https://ftp.iza.org/dp2961.pdf

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457–472. http://doi.org/10.1214/ss/1177011136

Glöckner, A., Hilbig, B. E., Henninger, F., & Fiedler, S. (2016). The reversed description–experience gap: Disentangling sources of presentation format effects in risky choice. *Journal of Experimental Psychology: General*, *145*(4), 486–508. https://doi.org/10.1037/a0040103

Glöckner, A., & Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. *Cognition*, *123*(1), 21–32. https://doi.org/10.1016/j.cognition.2011.12.002

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x

Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523. https://doi.org/10.1016/j.tics.2009.09.004

Hertwig, R., Hogarth, R. M., & Lejarraga, T. (2018). Experience and description: Exploring two paths to knowledge. *Current Directions in Psychological Science*, *27*(2), 123–128. https://doi.org/10.1177/0963721417740645

Hertwig, R., & Pleskac, T. J. (2010). Decisions from experience: Why small samples? *Cognition*, *115*(2), 225–237. https://doi.org/10.1016/j.cognition.2009.12.009

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655. https://doi.org/10.1257/000282802762024700

Hsee, C. K. (1996). The evaluability hypothesis: An explanation for preference reversals between joint and separate evaluations of alternatives. *Organizational Behavior and Human Decision Processes*, *67*(3), 247–257. http://doi.org/10.1006/obhd.1996.0077

Hsee, C. K., Loewenstein, G. F., Blount, S., & Bazerman, M. H. (1999). Preference reversals between joint and separate evaluations of options: A review and theoretical analysis. *Psychological Bulletin*, *125*(5), 576–590. https://doi.org/10.1037/0033-2909.125.5.576

Johnson, E. J., Steffel, M. Goldstein, D. G. (2005). Making better decisions: From measuring to constructing preferences. *Health Psychology*, *24*(4, Suppl), S17–S22. https://doi.org/10.1037/0278-6133.24.4.S17

Kellen, D., Pachur, T., & Hertwig, R. (2016). How (in)variant are subjective representations of described and experienced risk and rewards? *Cognition*, *157,* 126–138. https://doi.org/10.1016/j.cognition.2016.08.020

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(33), 13852–13857. https://doi.org/10.1073/pnas.1101328108

Kruschke, J. K., & Vanpaemel, W. (2015). Bayesian estimation in hierarchical models. In J. R. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), *The Oxford handbook of computational and mathematical psychology* (pp. 279–299). Oxford University Press.

Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian cognitive modeling: A practical course.* Cambridge University Press.

Lejarraga, T. (2010). When experience is better than description: Time delays and complexity. *Journal of Behavioral Decision Making*, *23*(1), 100–116. https://doi.org/10.1002/bdm.666

Lejarraga, T., & Gonzalez, C. (2011). Effects of feedback and complexity on repeated decisions from description. *Organizational Behavior and Human Decision Processes*, *116*(2), 286–295. https://doi.org/10.1016/j.obhdp.2011.05.001

Lejarraga, T., Hertwig, R., & Gonzalez, C. (2012). How choice ecology influences search in decisions from experience. *Cognition*, *124*(3), 334–342. https://doi.org/10.1016/j.cognition.2012.06.002

Lichtenstein, S., & Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *Journal of Experimental Psychology*, *89*(1), 46–55. https://doi.org/10.1037/h0031207

Lichtenstein, S., & Slovic, P. (2006). *The construction of preference*. Cambridge University Press.

Markant, D., Pleskac, T. J., Diederich, A., Pachur, T., & Hertwig, R. (2015). Modeling choice and search in decisions from experience: A sequential sampling approach. In D. C. Noelle, R. Dale, A. S. Warlaumont, J. Yoshimi, T. Matlock, C. D. Jennings, & P. P. Maglio (Eds.), *Proceedings of the 37th Annual Conference of the Cognitive Science Society* (pp. 1512–1517). Cognitive Science Society.

Markman, A. B., & Gentner, D. (1993). Structural alignment during similarity comparisons. *Cognitive Psychology*, *25*(4), 431–467. https://doi.org/10.1006/cogp.1993.1011

Mehlhorn, K., Ben-Asher, N., Dutt, V., & Gonzalez, C. (2014). Observed variability and values matter: Toward a better understanding of information search and decisions from experience. *Journal of Behavioral Decision Making*, *27*(4), 328–339. https://doi.org/10.1002/bdm.1809

Nilsson, H., Rieskamp, J., & Wagenmakers, E.-J. (2011). Hierarchical Bayesian parameter estimation for cumulative prospect theory. *Journal of Mathematical Psychology*, *55*(1), 84–93. https://doi.org/10.1016/j.jmp.2010.08.006

Nilsson, H., Rieskamp, J., & Wagenmakers, E.-J. (2020). Hierarchical Bayesian parameter estimation for cumulative prospect theory. *Journal of Mathematical Psychology*, *98,* Article 102429. https://doi.org/10.1016/j.jmp.2020.102429

Pachur, T., & Scheibehenne, B. (2012). Constructing preference from experience: The endowment effect reflected in external information search. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(4), 1108–1116. https://doi.org/10.1037/a0027637

Payne, J. W., Bettman, J. R., & Schkade, D. A. (1999). Measuring constructed preferences: Towards a building code. *Journal of Risk and Uncertainty*, *19*, 243–270. https://doi.org/10.1023/A:1007843931054

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science*, *17*, 407–413. https://doi.org/10.1111/j.1467-9280.2006.01720.x

Rieskamp, J. (2008). The probabilistic nature of preferential choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(6), 1446–1465. https://doi.org/10.1037/a0013646

Rouder, J. N., & Lu, J. (2005). An introduction to Bayesian hierarchical models with an application in the theory of signal detection. *Psychonomic Bulletin & Review*, *12*, 573–604, https://doi.org/10.3758/BF03196750

Scheibehenne, B., & Pachur, T. (2015). Using Bayesian hierarchical parameter estimation to assess the generalizability of cognitive models of choice. *Psychonomic Bulletin & Review*, *22*(2), 391–407. https://doi.org/10.3758/s13423-014-0684-4

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *64*(4), 583–639. https://doi.org/10.1111/1467-9868.00353

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, *32*, 101–130. https://doi.org/10.1007/s11166-006-8289-6

Su, Y.-S., & Yajima, M. (2020). *R2jags: Using R to run "JAGS"* (R package Version 0.5-7) [Computer software]. https://cran.r-project.org/web/packages/R2jags/R2jags.pdf

Trautmann, S. T., & van de Kuilen, G. (2015). Ambiguity attitudes. In G. Keren & G. Wu (Eds.), *The Wiley Blackwell handbook of judgment and decision making* (Vol. 1, pp. 89–116). Wiley-Blackwell.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574

Tversky, A., Sattath, S., & Slovic, P. (1988). Contingent weighting in judgment and choice. *Psychological Review*, *95*, 371–384. https://doi.org/10.1037/0033-295X.95.3.371

Ungemach, C., Chater, N., & Stewart, N. (2009). Are probabilities overweighted or underweighted when rare outcomes are experienced (rarely)? *Psychological Science*, *20*(4), 473–479. https://doi.org/10.1111/j.1467-9280.2009.02319.x

Walasek, L., & Stewart, N. (2015). How to make loss aversion disappear and reverse: Tests of the decision by sampling origin of loss aversion. *Journal of Experimental Psychology: General*, *144*(1), 7–11. https://doi.org/10.1037/xge0000039

Weber, E. U., Shafir, S., & Blais, A.-R. (2004). Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation. *Psychological Review*, *111*(2), 430–445. https://doi.org/10.1037/0033-295X.111.2.430

Weiss-Cohen, L., Konstantinidis, E., & Harvey, N. (2021). Timing of descriptions shapes experience-based risky choice. *Journal of Behavioral Decision Making*, *34*, 66–84. https://doi.org/10.1002/bdm.2197

Weiss-Cohen, L., Konstantinidis, E., Speekenbrink, M., & Harvey, N. (2016). Incorporating conflicting descriptions into decisions from experience. *Organizational Behavior and Human Decision Processes*, *135*, 55–69. https://doi.org/10.1016/j.obhdp.2016.05.005

Weiss-Cohen, L., Konstantinidis, E., Speekenbrink, M., & Harvey, N. (2018). Task complexity moderates the influence of descriptions in decisions from experience. *Cognition*, *170*, 209–227. https://doi.org/10.1016/j.cognition.2017.10.005

Wulff, D. U., Mergenthaler-Canseco, M., & Hertwig, R. (2018). A meta-analytic review of two modes of learning and the description–experience gap. *Psychological Bulletin*, *144*(2), 140–176. https://doi.org/10.1037/bul0000115

Chapter 3:
The Trade-Off between the Costs and Benefits of Time

Good Time, Bad Time: Do People Invest Processing Effort Adaptively in Decision Making with Opportunity Costs?

Kevin E. Tiede[1,2], Veronika Zilker[3], & Thorsten Pachur[3]

[1]Graduate School of Decision Sciences, University of Konstanz
[2]Department of Psychology, University of Konstanz
[3]Center for Adaptive Rationality, Max Planck Institute for Human Development

This research was funded by the Max Planck Institute for Human Development and the Graduate School of Decision Sciences at the University of Konstanz.

Abstract

When making choices, deliberation time is often costly but also promises to improve decision making. This, however, applies only if the available options differ in attractiveness, as additional processing time might not be worthwhile if the options yield similar value. We investigate to what extent people respond to the costs and benefits of time adaptively under varying value differences between options in decisions under risk. The drift diffusion model (DDM) serves as a computational framework to study the trade-off between costs and benefits of time. Based on simulations we first determined how people should adapt their boundary separation in order to maximize payoffs depending on the differences in options' value and the magnitude of opportunity costs (i.e., loss in payoff per time unit). Subsequently, we conducted three empirical experiments to study if people adjust their processing adaptively, in line with the simulations. Across all experiments, participants' estimated boundary separations were mostly sensitive to the presence (vs. absence) of opportunity costs, but less so to different levels of cost. As a result, people did not adapt their boundaries to the differences between option value optimally, with boundaries being narrower than optimal when value differences were relatively large and wider than optimal when value differences were relatively small. Although guessing would be most beneficial in some conditions, participants did not adopt a guessing strategy in any condition. In conclusion, people seem to have limited abilities to adjust their information processing adaptively to the magnitude of the opportunity costs and value differences.

3.1 Introduction

When making decisions, time often matters. Time spent making one decision could be invested in making another, or payoffs become less available or attractive over time. On the other hand, taking more time also can improve a decision, because longer deliberation can lead to more accurate processing of the options. Decision makers thus have to trade off the benefits of further deliberating against the costs of time. Investigations on risky choice have shown that people make faster and less accurate choices when there are opportunity costs of time (Hausfeld & Resnjanskij, 2018; Payne et al., 1996; Rieskamp & Hoffrage, 2008), but less is known about how adaptive this response is. Our research aims to study how adaptively people trade off the benefits and costs of time when making decisions under risk with opportunity costs of time.

One prominent approach to study how different choice strategies trade off cognitive effort against accuracy is the Adaptive Decision Maker framework (Payne et al., 1993). In this framework, effort is operationalized as the number of different mental operations (e.g., reading or comparing information) and accuracy is measured as the relative accuracy compared to guessing and an optimal expected-value-maximizing strategy. Because the value of effort and accuracy depends heavily on the subjective weights decision makers assign to reducing effort and increasing accuracy, different weights can lead to different conclusions about the optimal choice strategy (Payne et al., 1993, 1996).

Sequential sampling models (SSMs) offer a solution to explicitly model the trade-off between the costs and benefits of time. By striving to maximize accuracy, they do not require subjective weights to identify an optimal strategy. Arguably the most prominent SSM is the drift diffusion model (Ratcliff, 1978, Ratcliff & McKoon, 2008), a model for binary decisions according to which information is accumulated with some noise over time. The accumulation continues until a boundary is reached, initiating a response (see Figure 3.1). Each boundary corresponds to one option. Here, we assume that the upper boundary corresponds to the higher-valued option. The decision process is described by three parameters. The rate of information accumulation is governed by the *drift rate* δ. The drift rate reflects the rate of evidence accumulation and is assumed to be mainly determined by the difficulty of the task (i.e., how easily options can be discriminated; Ratcliff & McKoon, 2008). In the current case, a higher (vs. lower) drift rate leads to

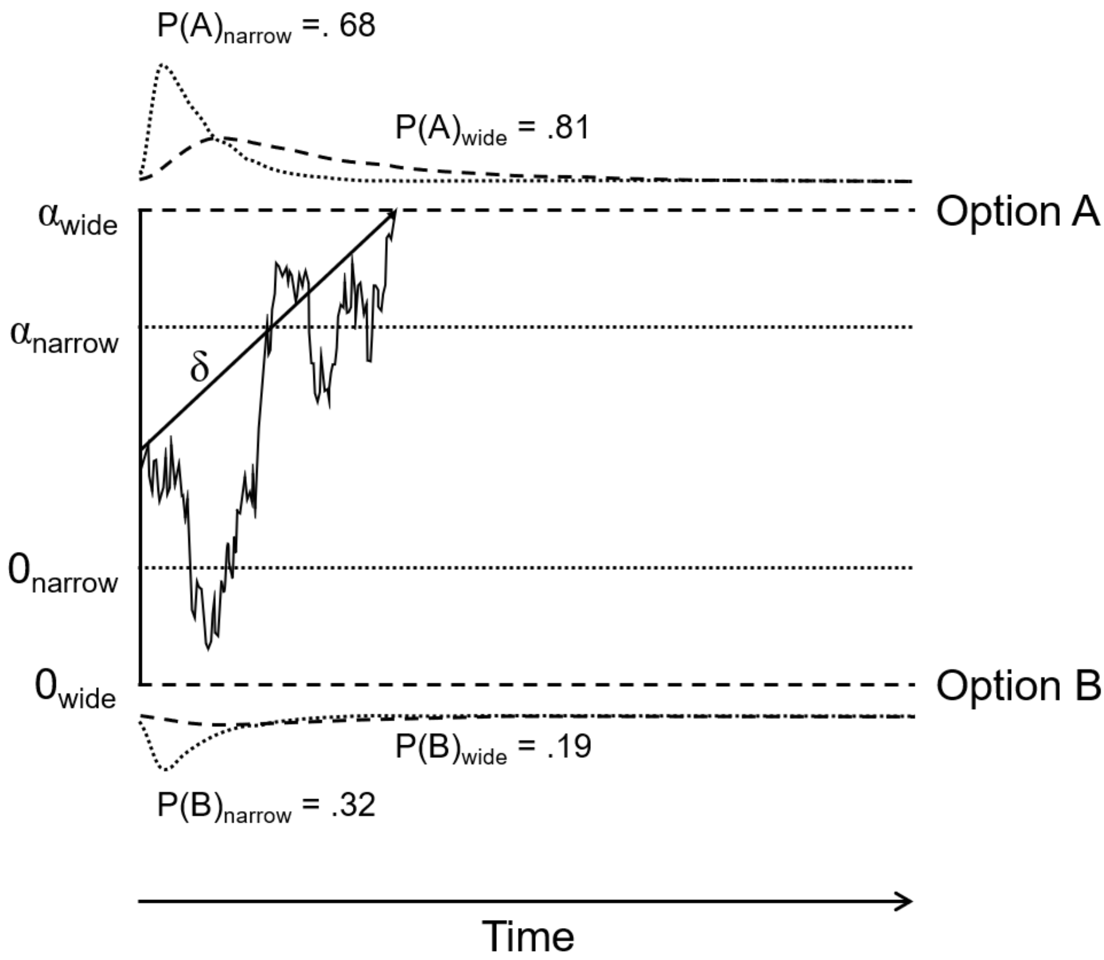

Figure 3.1: Illustration of the information accumulation process of the drift diffusion model (DDM) and its dependency on the boundary separation. Narrow boundaries (dotted lines) lead to faster choices, but to a lower proportion choosing the superior option A, P(A), than wide boundaries (dashed lines).

decisions which are faster and more accurate (i.e., choose the higher-valued option more often). The distance between the boundaries is captured by the *boundary separation* parameter α. The boundary separation is assumed to capture the decisions maker's conservatism (Voss et al., 2004). The DDM can thus implement a speed-accuracy trade-off, with wider boundaries leading to slower but more accurate choices (see Figure 3.1). Some implementations of the DDM involve a *bias* parameter β which moves the starting point of accumulation closer to one of the boundaries. We do not, because we do not expect an a priori bias towards any of the two options. Finally, the *non-decision time* τ captures components of the overall response time which are not part of the deliberation process (e.g., the time needed to encode information or to move the fingers).

As illustrated in Figure 3.1, different combinations of parameter values lead to different predictions about the proportions of choices of both options and response times. Given particular values of both options, it is possible to determine the average payoff under each combination of parameter values. If time is free (i.e., there are no opportunity costs of time), this payoff will be the larger the wider boundaries are. However, if there are opportunity costs and thus every unit of time leads to a certain loss in payoff, increasing boundary separation may improve accuracy but can lead to excessive losses in payoff if boundaries are too wide. On the other hand, narrowing down boundaries avoids excessive opportunity costs, but can lead to a higher probability of inaccurate choices and thus losses. Therefore, in decisions with opportunity costs of time, there exists a boundary separation which trades off the costs and benefits of time most efficiently and maximizes expected payoff.

The optimal boundary separation, in turn, depends on the level of opportunity costs and the difference between the options' values. To examine how people should adapt their boundary separations, we conducted a computer simulation in which we computed the expected payoff given different combinations of DDM parameter values as

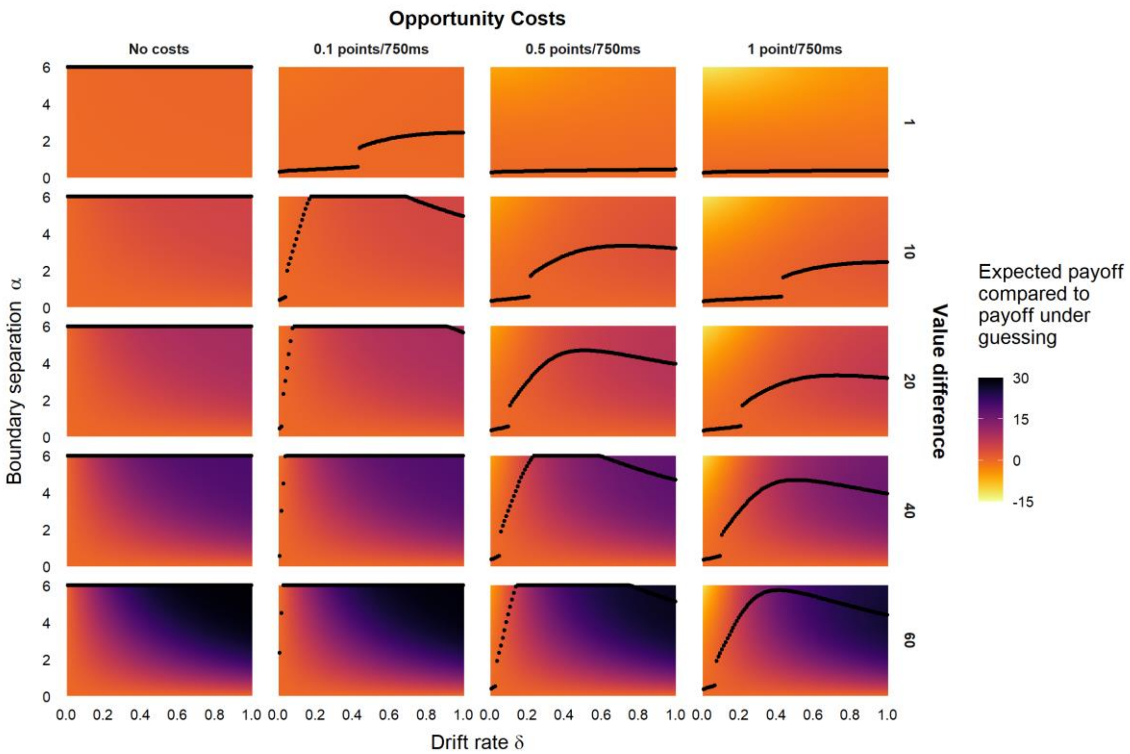

Figure 3.2: Simulated expected payoffs as a function of drift rate, boundary separation, opportunity costs, and value differences. Black points indicate boundary separations which lead to the highest expected payoff given different values of the drift rate δ.

well as different levels of value differences and opportunity costs (for details, see Methods). The results of this simulation are illustrated in Figure 3.2. The higher the opportunity costs (i.e., reading Figure 3.2 from left to right), the lower the boundary separation generally should be to maximize payoffs. Furthermore, the optimal boundary separation is also affected by the differences between the values of the options. If the value differences are very small (e.g., differ by 1 point; top row of Figure 3.2), boundaries close to 0 are optimal because there is little to gain through deliberating. Boundaries close to 0, in turn, reflect guessing because the information accumulation process hits a boundary directly after the start. The larger the differences between values become (i.e., reading Figure 3.2 from top to bottom), the more profitable deliberation becomes because larger value differences offer larger payoffs relative to guessing. In addition, larger value differences are usually associated with larger drift rates which result in higher benefits of deliberation time, so that wider boundaries become more optimal with increasing drift rates (i.e., reading each tile of Figure 3.2 from left to right).

The DDM has been previously used to study decision making with opportunity costs of time in different domains of decision making. In risky choice, boundary separations have been shown to become smaller the higher opportunity costs are (Hausfeld & Resnjanskij, 2018). However, it is unclear how adaptive this adjustment of boundary separation is. Other studies have investigated this adaptivity in the domain of perceptual decision making. In most of these studies, participants view clouds of moving dots and are asked in which direction the majority of dots are moving. Opportunity costs are often implemented based on a time limit, such that faster participants can make more decisions. Findings of such studies are rather mixed: One study found that decision makers do not deviate from optimality (Jarvstad et al., 2012), whereas other studies demonstrated that people weight accuracy more heavily so that they deliberate longer than optimal (Bhui, 2019; Bogacz et al., 2010; Starns & Ratcliff, 2010, 2012). Other studies showed that initially too-cautious decisions can become more optimal under certain conditions (e.g., with feedback or practice; Balci et al., 2011; Evans et al., 2019; Evans & Brown, 2017; Simen et al., 2009).

Fewer studies have investigated how adaptive boundary separations are given different value differences. In value-based decision making between food items with opportunity costs, people have been shown to decide longer given smaller value differences (Oud et al., 2016), a pattern usually observed in decisions without opportunity costs (Krajbich et al., 2010; Krajbich & Rangel, 2011). However, this pattern is the opposite of what would have been optimal according to the argumentation of the study and our simulation (Figure 3.2). Implementing the DDM, a study on perceptual decision making showed that this pattern could also be found when estimating boundary separations: options which were harder to discriminate led to wider boundaries (Starns & Ratcliff, 2012).

Moreover, our simulation demonstrated that guessing is an adaptive strategy when value differences are small. However, previous studies investigating time trade-offs did not consider guessing as adaptive, but even as thoughtless behavior, leading to exclusion of respective participants (Evans et al., 2019; Evans & Brown, 2017; Fiedler et al., 2021; Starns & Ratcliff, 2012).

Our research aims to study systematically how adaptively people set their boundary separation given different levels of opportunity costs and value differences when making decisions under risk. The studies on perceptual decision making provide support for our computational approach, but their conclusions for risky choice may be limited because perceptual decisions have been argued to be more optimal than more cognitive risky choice tasks (Trommershäuser et al., 2008; but see Jarvstad et al., 2012).

3.2 Results

Our research aimed to investigate how people trade off the costs and benefits of time when making risky choices. For this purpose, we examined whether people adjust their information processing adaptively to the level of opportunity costs and value differences in line with our simulations by conducting three empirical experiments (for details, see Methods following the General Discussion).

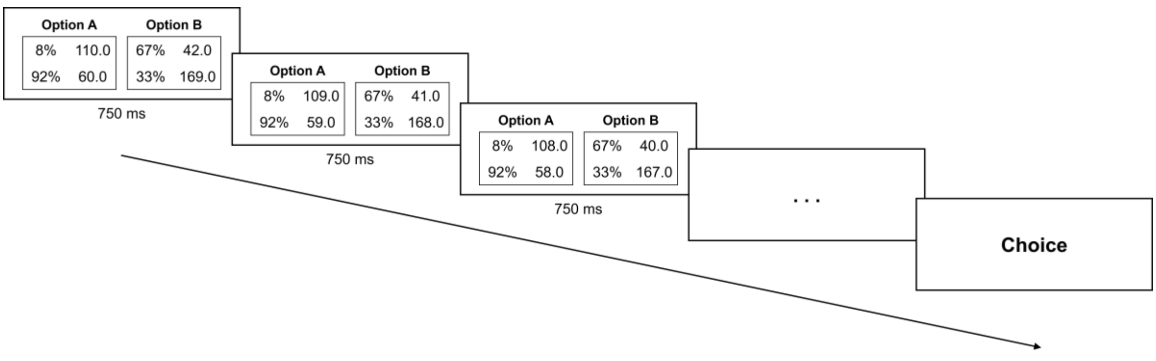

Figure 3.3: Schematic illustration of a choice trial with opportunity costs of time (here: 1 point per 750 ms).

3.2.1 Experiment 1

The goal of Experiment 1 was to study whether people adapt their information processing optimally, as identified in the simulation. Participants made 10 practice and 40 main decisions between two risky gambles with two outcomes each. We manipulated opportunity costs and value differences between participants. In the no-opportunity-costs conditions, outcome values remained fixed over time. In the low- and high-opportunity-costs conditions, outcome values decreased by a low and high amount, respectively, every 750 ms (see Figure 3.3). Further, option values were reflected by options' expected values (EVs) and differences between them were either large, moderate, or small. We modeled choices and response times using a Bayesian hierarchical implementation of the DDM and compared the boundary separation parameter estimates to the optimal values of α identified in the simulations for the same condition.

3.2.1.1 Behavioral Results

Accuracy was higher when value differences were larger ($F(2,262) = 67.42$, $p < .001$) and when opportunity costs were lower ($F(2,262) = 11.30$, $p < .001$; for detailed results, see Supplemental Materials, Figure S2.4). Response times are displayed in Figure 3.4. There was no effect of value differences on response times ($F(2,262) = 0.39$, $p = .675$),

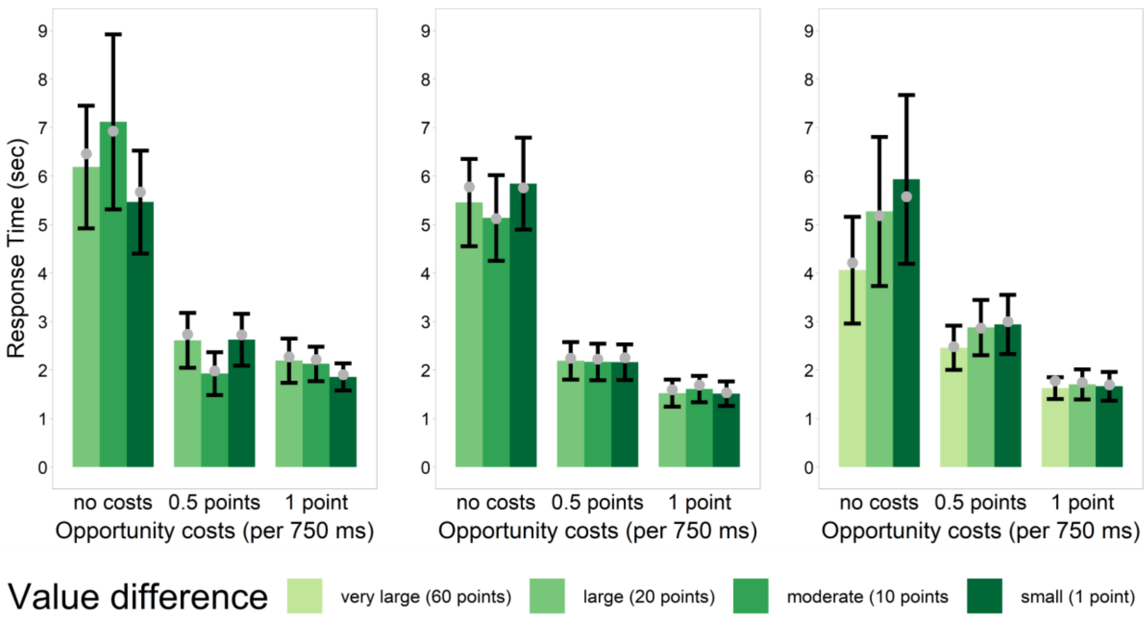

Figure 3.4: Response times in each condition (error bars represent 95% confidence intervals) for Experiment 1 (left panel), Experiment 2 (middle panel), and Experiment 3 (right panel). Grey points represent means of the posterior predictive checks generated by the estimated DDM parameters.

but there was a significant effect of opportunity costs ($F(2,262) = 73.55$, $p < .001$). A posthoc analysis revealed that this effect was driven by the difference between the no-opportunity-costs condition and the two opportunity-costs conditions, as there was no difference in response times between the high- and low-opportunity-costs conditions.

3.2.1.2 Modeling Results

The drift rate δ of the DDM was higher when the differences between options' EVs were larger (i.e., all differences between value-difference conditions were credible). Importantly, drift rates did not differ between opportunity costs conditions (i.e., no differences were credible; see Supplemental Materials, Figure S2.5). As illustrated in Figure 3.5, boundary separation α was not affected by differences in option value, as the α did not credibly differ between value-difference condition within the opportunity-costs conditions. However, opportunity costs affected α. Specifically, participants set credibly narrower boundaries when there were opportunity costs (vs. no opportunity costs), but boundary separation did not credibly differ between conditions with low and high opportunity costs.

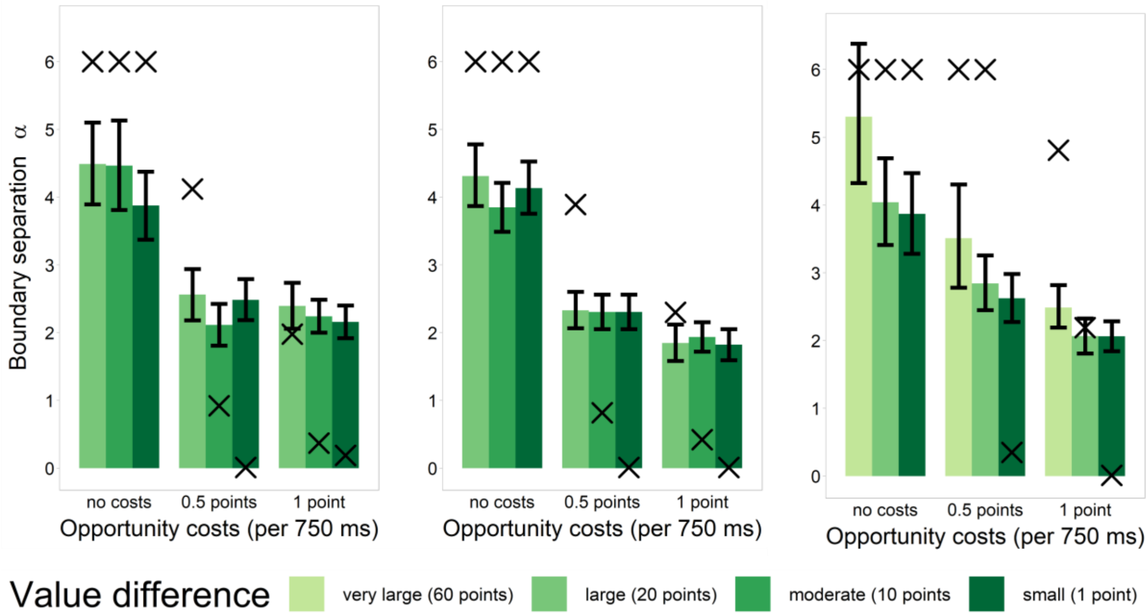

Figure 3.5: Estimated boundary separation α (group-level posterior means; error bars represent 95% HDIs) and optimal boundary separation α (indicated by ×) in each condition for Experiment 1 (left panel), Experiment 2 (middle panel), and Experiment 3 (right panel). Because the optimal α in the no-costs conditions is infinite and we modeled values of the optimal α ranging from 0.01 to 6.00, the optimal α in the no-costs conditions reaches the limit of this range at 6.00.

Next, we compared the estimated boundary separations to those maximizing expected payoffs in each condition. In the absence of opportunity costs, wider boundaries are generally preferable. Therefore, we focus on the conditions with opportunity costs. As shown in Figure 3.5, when there are opportunity costs, the optimal boundary separation (marked with a ×) depends on both the value differences and magnitude of opportunity costs. In particular, boundaries should be narrower given smaller value differences and higher opportunity costs. The 95% HDI of estimated boundary separations did not include the optimal boundary separation in any of the opportunity-costs conditions, suggesting non-adaptive adjustment of information processing. In one of the six conditions with opportunity costs (i.e., large value differences and low opportunity costs), boundaries were narrower than optimal. In the other five conditions, including those in which guessing (i.e., α close to 0) was most beneficial, boundary separations were wider than optimal. Non-decision time τ did not differ between any of the conditions (see Supplemental Materials, Figure S2.6).

Next, we determined the expected payoff relative to guessing, obtained both based on the estimated and optimal boundary separations, and in each condition (see

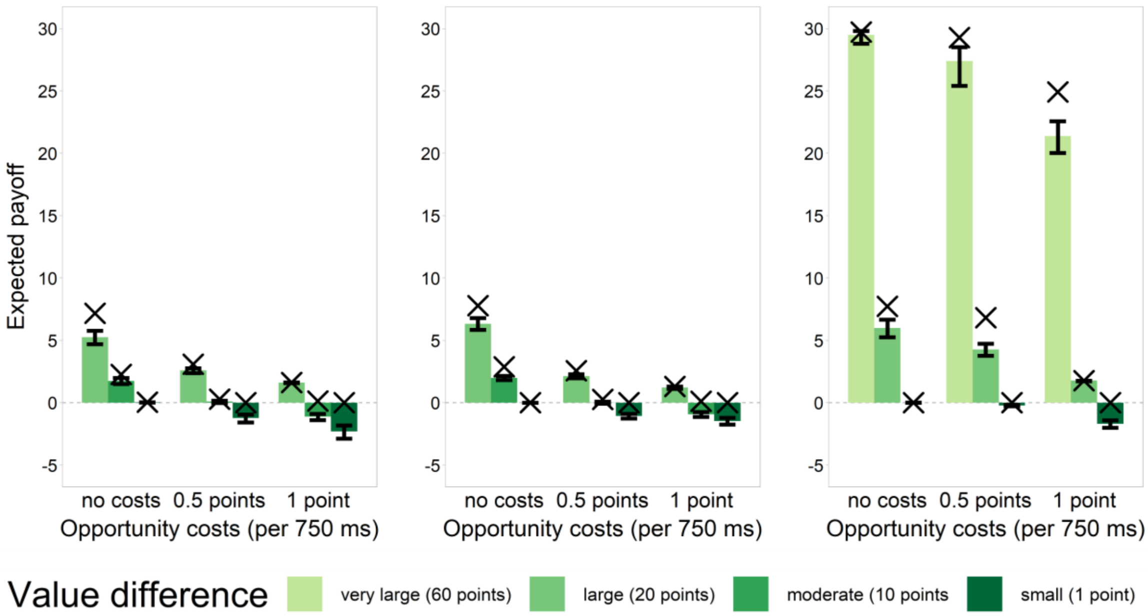

Figure 3.6: Expected payoff in each condition relative to guessing (given the group-level posterior mean and, as shown by the error bars, the 95% HDIs of the respective boundary separations α), together with the expected payoff under optimal α (indicated by ×) in each condition for Experiment 1 (left panel), Experiment 2 (middle panel), and Experiment 3 (right panel).

Figure 3.6). In all conditions with opportunity costs, participants earned fewer points than expected under optimal boundary separations, although the losses in payoff were relatively small. In the conditions with small value differences participants even earned less than they would have if they had employed a guessing strategy.

The results of Experiment 1 show that people did not adapt their boundary separations to maximize payoffs under different levels of opportunity costs and varying value differences. Although guessing would have been the most profitable strategy in some of the conditions, participants did not adopt this strategy. Interestingly, and in contrast to findings on perceptual decision making, participants did not exhibit a general tendency to set wider boundaries than optimal; instead, boundaries were narrower than optimal in choices with large value differences and low opportunity costs, but wider than optimal in choices with moderate to small value differences and/or high opportunity costs.

3.2.2 Experiment 2

Sensitivity to value differences and thus adaptivity may have been limited in Experiment 1 because, due to the between-subjects manipulation of value differences, each participant experienced only one level of value differences. To test whether the experience of different degrees of value differences would improve sensitivity to them, we repeated Experiment 1 but varied value differences within participants. In Experiment 2, there were again three value differences, but value difference varied between blocks. Participants were not told in which regard the choice problems in each block differed, but they had the chance to learn about the different types of choice problems in a practice phase before moving on to the main phase with 40 consequential choices in each block.

3.2.2.1 Behavioral Results

Again, accuracy was higher with increasing value differences ($F(2,174) = 137.19$, $p < .001$) and lower opportunity costs ($F(2,87) = 12.79$, $p < .001$; see Supplemental Materials, Figure S2.4). There was a significant interaction of value differences and opportunity costs, with smaller differences between value differences in choices with higher opportunity costs ($F(4,174) = 6.92$, $p < .001$). Response times are illustrated in Figure 3.4. Response times did not differ between value-difference conditions ($F(2,174) = 0.87$, $p = .423$), but were shorter when opportunity costs were higher ($F(2,87) = 62.69$, $p < .001$). The effect of opportunity costs on response times interacted with value differences, indicating lower sensitivity to value differences under higher opportunity costs ($F(4,174) = 2.71$, $p = .032$). Posthoc tests revealed that the differences in response times between the low- and high-opportunity-cost conditions were significant.

3.2.2.2 Modeling Results

Again, drift rates δ were higher given larger value differences and did not differ between opportunity-costs conditions (see Supplemental Materials, Figure S2.5). Boundary separations are illustrated in Figure 3.5. Again, boundary separation α was not affected by value differences (i.e., differences between value-difference conditions were not credible). However, in contrast to Experiment 1, boundary separation not only differed between conditions with and without opportunity costs, but also between the low- and high-opportunity-costs conditions (i.e., all differences between opportunity-costs conditions were credible). As in the previous experiment, non-decision time τ did not differ between any of the conditions (see Supplemental Materials, Figure S2.6).

Because the choice problems of Experiment 1 were used and thus the drift rates were expected to be similar to those in Experiment 1, the pattern of optimal boundary separation was also similar: Smaller value differences and higher opportunity costs required lower optimal boundaries to maximize payoffs. Again, estimated boundaries were narrower than optimal under large value differences and low opportunity costs and wider than optimal in the other conditions. Further, participants again did not guess when it was the most beneficial strategy.

As in Experiment 1, participants earned smaller payoffs than expected under optimal boundary settings, but the losses in payoff were again rather small (see Figure 3.6).

In sum, giving each participant the opportunity to experience different degrees of value differences did not enhance their sensitivity to these value differences, but it did increase the sensitivity to differences in opportunity costs to some extent.

3.2.3 Experiment 3

In the two previous experiments, people's boundary separations were not sensitive to value differences between options. In the following experiment, we test whether increasing the range of value differences would enhance the sensitivity to value differences. Our simulation demonstrated that the larger value differences are, the more profitable an adaptive setting of boundary separation becomes because there is more to gain in comparison to guessing. For instance, in a choice between two options with the values 90 and 110, people can only earn up to 10 points more than when guessing (i.e., which would, on average, result in 100 points). In a choice between options with the values 50 and 150, however, people can earn up to 50 points more compared to guessing. To test whether people would adapt better to value differences when more can be gained from behaving adaptively (i.e., when value differences are overall larger), we repeated Experiment 2 but used choice problems with very large value differences in addition to the previously used choice problems with large and small differences in value. Moreover, the following experiment aimed to further study the sensitivity to different levels of opportunity costs and to test whether very low opportunity costs affect boundary separations by an accordingly small degree or rather to a relatively large degree because the mere presence of opportunity costs evokes a strong reaction. For this purpose, we implemented a condition with very low opportunity costs and tested how boundary separations differed compared to conditions with no and high opportunity costs.

3.2.3.1 Behavioral Results

Again, accuracy was higher given larger value differences ($F(2,178) = 219.62$, $p < .001$) and given lower opportunity costs ($F(2,89) = 3.41$, $p = .037$; see Supplemental Materials, Figure S2.4). Accuracy varied less strongly across different degrees of value differences when opportunity costs were higher ($F(4,178) = 2.94$, $p = .022$). Response times are shown in Figure 3.4. People chose faster when differences in option value were larger ($F(2,178) = 8.53$, $p < .001$) and when opportunity costs were higher ($F(2,178) = 8.53$, $p < .001$). As in the previous experiment, value differences affected response times less strongly under higher opportunity costs ($F(4,178) = 3.98$, $p = .004$).

3.2.3.2 Modeling Results

Again, drift rates δ were higher with larger value differences, but were not affected by opportunity costs (see Supplemental Materials, Figure S2.5). Estimated and optimal boundary separations are illustrated in Figure 3.5. As in Experiment 2, boundary separations α were lower with higher opportunity costs and differed not only between conditions with and without opportunity costs, but also between those with low and high opportunity costs (i.e., all differences were credible). Boundary separations did not differ between the choices with large and small value differences which were already used in the previous two experiments (i.e., differences were not credible). However, boundary separations were sensitive to value differences when comparing the previously used choice problems with small and large value differences with those with very large differences which were newly implemented. In particular, boundary separations were now credibly higher in choices with very large value differences compared to those with small value differences in each of the conditions with the same magnitude of opportunity costs. Non-decision time τ did not differ between any of the conditions (see Supplemental Materials, Figure S2.6).

Again, to set boundaries in an optimal fashion, people should be sensitive to both opportunity costs and value differences between the options. Notably, when opportunity costs were very small, the optimal boundary separations for large and very large value differences were relatively high, indicating that participants could have ignored costs in these choices (but not in the ones with small differences). However, estimated boundaries in these two conditions as well as in the condition with very large value differences and high opportunity costs were narrower than optimal. In the two conditions in which guessing was optimal, estimated boundaries were wider than optimal, indicating a stronger than necessary response to the presence of opportunity costs. In one condition (i.e., large value differences and high opportunity costs), boundary separations were not credibly different from the optimal value, although boundary separations in the same condition of Experiments 1 and 2 were once narrower (Experiment 1) and once wider than optimal (Experiment 2).

Results on expected payoffs with estimated and optimal boundary separations showed that, again, participants lost out on points due to their limited adaptivity. These losses in payoff were largest in the conditions with very large value differences (see Figure 3.6).

The results of Experiment 3 suggest that decision makers can become somewhat sensitive to different degrees of value differences when values differ to a great extent and an optimal adaption of boundaries becomes particularly profitable. However, despite the increased sensitivity, estimated boundaries were still narrower than optimal in the choice problems with very large value differences. Moreover, opportunity costs which were so low that they could have been ignored still had a considerable effect on boundary separation, but to a lesser degree than the high opportunity costs. This suggests that people respond strongly to the presence of opportunity costs but at the same time are sensitive to the specific costs of time.

3.3 General Discussion

In many decisions, taking time to deliberate is costly but can also improve the choice. Therefore, decision makers have to trade off the costs and benefits of time while taking the difference in option value into account. In this article, we present an approach to quantitatively study this trade-off in the domain of risky choice and investigate how adaptively people adjust their information processing to the magnitude of opportunity costs and differences between the options' values. Using the DDM as a computational framework, we first conducted a simulation which demonstrated that both differences in option value and the level of opportunity costs have to be considered when setting the boundary separation in order to maximize payoffs. Next, we investigated whether people adapted their boundary separations as identified in the simulation. In three empirical experiments, participants made risky choices with different magnitudes of opportunity costs and value differences. Across all experiments, people showed only limited sensitivity to differences in value differences and different magnitudes of opportunity costs. As a result, estimated boundary separations deviated from the optimal ones: boundaries were narrower than optimal when value differences were large and wider than optimal when differences were small. Participants did not guess by setting boundaries close to 0 when this was warranted. Together, these results suggest that people barely adapt their choice criterion to opportunity costs and differences in option value.

One explanation for the limited sensitivity to value differences is that in the first two experiments, behaving optimal was not sufficiently rewarded, seen by small losses caused by deviation from optimality (see Figure 3.6). When people chose between options which differed substantially in value and thus adaptivity offered a relatively large reward, people adjusted their boundary separations accordingly. Thus, people may become sensitive to value differences only if adaption is rewarded sufficiently. Another explanation for our findings is that people do not understand that and how boundary separations should depend on value differences. This notion is supported by a study on perceptual decision making which provided people with feedback on ways to improve their performance (e.g., by reducing decision time by a certain amount) and the consequences thereof (Evans & Brown, 2017). Participants had higher payoffs when they were provided with this detailed feedback than when they were only informed about their performance or received no feedback. This shows that in principle, people are able to learn how to behave more optimally if they are told how to. Finally, people could have pursued other goals than to maximize expected payoffs which the DDM is geared towards. People could have behaved in accordance with other, subjective goals (e.g., avoiding risks when deliberation time is costly) which our implementation of the DDM could not reflect due to the definitions of the boundaries.

Whereas previous research on perceptual decision making has concluded that people allocate time show a general trend towards choosing too cautiously compared to optimal behavior (Bhui, 2019; Bogacz et al., 2010; Starns & Ratcliff, 2010, 2012), we did not find a general direction of deviation from optimality. Rather, people seemed to set narrower boundaries than optimal when value differences were large and wider boundaries when value differences were small. One way to interpret the difference between these findings and ours would be to attribute these differences to differences in the domain, which would suggest that people trade off costs and benefits of time differently in perceptual and cognitive decision making (Trommershäuser et al., 2008). However, an alternative account is that people are rather insensitive to differences in option value and the conclusions drawn about too-cautious decision making are rather a result of the study designs (e.g., presenting options which are relatively hard to discriminate) rather than a true tendency. For instance, Balci et al. (2011) also found no differences in estimated boundary separation between conditions with varying difficulty when studying perceptual decision making. Evans et al. (2019) have already argued that previous studies have rewarded too-cautious choice strategies more strongly than too-urgent ones. In an experiment, they could show that increasing the relative reward for too-urgent (vs. too-cautious) choices shifted boundary separations closer to optimality, although participants did not exhibit a tendency for too-urgent choices. Our findings support the argumentation that findings on decision making with opportunity costs may be at least partly affected by the study design and thus conclusions about optimality or deviation from it have to consider the environment in which choices are being made.

Our simulations showed that guessing (i.e., a boundary separation close to 0) can be an adaptive choice strategy under certain conditions, in particular when choosing between options which differ only little in value. In contrast, many studies on risky choice consider guessing as inattentive or as not complying with the instructions, resulting in an exclusion of participants who seem to be guessing (e.g., Evans et al., 2019; Evans & Brown, 2017; Fiedler et al., 2021; Starns & Ratcliff, 2012). Our findings show that people who seem to guess in studies may actually behave adaptively. For instance, studies often involve implicit opportunity costs of time (e.g., by offering a fixed compensation which is independent of individual study duration). When options only differ in value to a certain amount or correct choices are not rewarded sufficiently, guessing may well be the most adaptive strategy. Our findings encourage future research to examine the potential benefits of guessing and to interpret guessing not necessarily as undesirable, but potentially as highly adaptive.

In conclusion, our findings suggest that deviation from optimality might not be caused by a general tendency to choose too cautiously (Rahnev & Denison, 2018), but rather by a limited sensitivity to the difference in options values which can cause deviation from optimality in both directions—leading to choices which are more cautious or more urgent than optimal, depending on the size of value differences. Therefore, this research demonstrates that it is necessary to take into account the features of the choice environment when interpreting findings on the time trade-off to provide deeper insights into the way people deal with time when making decisions.

3.4 Methods

3.4.1 Simulation

In the simulation described in the Introduction, we examined how the expected payoff depends on parameter values of the DDM (i.e., drift rate and boundary separation) as well as opportunity costs and value differences. First, we simulated response times for both options given different combinations of drift rate δ and boundary separation α. We defined the upper boundary as the option with the higher value and the lower boundary as the option with the lower value. We orthogonally varied δ from 0.01 to 1.00 in steps of 0.01 and α from 0.01 to 6.00 in steps of 0.01. Non-decision time τ was fixed to 0.60 (a typical value observed in our experiments). The bias parameter β was fixed to 0.50 because there was no reason to believe that choices would be shifted a priori towards a particular option. For each combination of DDM parameter values, we computed the proportion of people who chose the higher-valued and the lower-valued option in each 750 ms time period. Then, depending on value-difference condition, we assigned different values to both options, using the 40 choice problems used in Experiment 3, with the options' EVs being their value. The differences in EVs were 1, 10, 20, 40, and 60. Further, we orthogonally varied the level of opportunity costs. Costs were 0 points (i.e., no costs), 0.1 points, 0.5 point, or 1 point per 750 ms. Then, we multiplied the choice proportion in each 750 ms period with the value of the chosen option in that period considering the opportunity costs. Summing up across all time periods and averaging across choice problems within each parameter setting and condition (i.e., a given level of opportunity costs and a given EV difference) yields the expected payoff of a choice strategy based on the assumed DDM parameters in that condition.

3.4.2 Experiments 1, 2, and 3

Besides differences in the experimental conditions, the design and participant recruitment of the three experiments were similar. All experiments were approved by the ethics committee of the Max Planck Institute for Human Development.

3.4.2.1 Participants

All participants were recruited online via the platform Prolific Academic. An inclusion criterion was to speak English fluently. Participants could not participate in more than one of the three experiments. For compensation, participants received a flat fee of £1.00 (Experiment 1) or £3.50 (Experiments 2 and 3) and a performance-contingent bonus of, on average, £0.51, £1.05, and £1.80 (Experiments 1, 2, and 3, respectively; for details on how the bonus was determined, see below). Participants who did not pass the attention check (20, 2, and 5 participants in Experiments 1, 2, and 3, respectively) did not receive any payment and were not considered for the analyses.

3.4.2.2 Choice Task

In all experiments, the choice task consisted of a practice and a main phase. Choices in the practice phase gave participants the chance to learn about the types of choice problems and had no consequences, whereas in the main phase new choice problems of the same types were presented and choices were relevant to the determination of the bonus. In both phases, participants repeatedly chose between two monetary gambles with two outcomes each. Participants were asked to choose the option they preferred by pressing a key corresponding to that option on their keyboard (i.e., S for left option, L for right option). In the opportunity-costs conditions, outcome values decreased every 750 ms by a particular amount. The displayed outcome values were updated accordingly every 750 ms, so that participants could always see the potential outcomes they could obtain if they made a choice at that particular point in time. As soon as an outcome reached 0, it remained at 0 (however, in the main phase all participants made all their choices before any outcome reached 0). In the conditions without opportunity costs, the outcomes remained fixed. In all conditions, after participants made their decision, the chosen gamble was played, and participants received feedback on their payoff for 1000 ms. Following a blank screen displayed for 400 ms, a new choice problem was presented. Screenshots of choice screens of the experiments can be found in the Supplemental Materials and a video showing a choice trial with opportunity costs can be found at https://osf.io/n6bwm/?view_only=ad1144c347d14c0492ac3bfa4142d1d8.

3.4.2.3 Choice Problems

Choice problems of both the practice and main phase were pseudorandomly generated with the restrictions that there were two outcomes, outcomes ranged from 20 to 200 points, neither option stochastically dominated the other, and the options' values in terms of EVs differed by a targeted amount (+/- 0.1 points). To vary EV differences while holding other choice problem features constant, we randomly generated a set of original choice problems with the largest EV difference used in a study. Next, we decreased the difference between the options' EVs in each choice problem by adding a certain number of points to one option's outcome values and subtracting the same amount from the other option's outcome values. By varying the options' EVs symmetrically around their mean, we ensured that the choice problems mainly varied in the difference in EVs, but not in the mean of the two options' values. Therefore, guessing would result in the same expected payoff for all conditions, so that the propensity to guess would not differ between conditions due to differences in choice problems (choice problems used in all experiments can be found here: https://osf.io/n6bwm/?view_only=ad1144c347d14c0492ac3bfa4142d1d8)

3.4.2.4 Procedure

In all experiments, participants first provided informed consent and received instructions. Then, they completed the choice task with a practice and a main phase. Participants were told that at the end of the study, one trial of the main phase would be randomly selected and played out, and they would receive the payoff converted into money as a bonus (Experiment 1: 2 points = £0.01; Experiments 2 and 3: 1 point = £0.01) in addition to the baseline payment for participation. After the main phase, participants completed an attention check which was announced at the beginning of the study. Participants were instructed that they would make five choices between two options without opportunity costs and that they would have to choose the higher-valued option in at least four out of five times to complete the study and receive the payment. In all five choice problems, one option stochastically dominated the other. Finally, participants entered their demographics (age, gender, and highest educational degree), indicated whether they were color blind (in Experiments 2 and 3 only), and received information on their bonus.

3.4.2.5 Statistical Analysis of Behavioral Data

To examine how accuracy and response times differ between conditions, for each study we conducted two ANOVAs with opportunity cost level, value differences, and their interaction as predictors and proportion of choices in line with EV maximization and, to account for commonly skewed response time distributions, log-transformed response times as outcome variable, respectively. In Experiment 1, both predictors were between-subjects factors, whereas in Experiments 2 and 3, value difference was a within-subjects factor and opportunity-cost level was a between-subjects factor.

3.4.2.6 Computational Modeling

We used a hierarchical Bayesian implementation of the DDM to model choices and response times. In Bayesian parameter estimation, parameters are initially represented in terms of prior distributions which are then updated into posterior distributions based on the observed data (Kruschke, 2014). In hierarchical Bayesian modeling, parameters are estimated for each subject and subject-level parameters are assumed to be drawn from a group-level distribution. Thereby, the approach finds an optimal compromise between complete pooling of group data and complete independence of subjects within a group, yielding more reliable and accurate estimates than non-hierarchical approaches (e.g., Kruschke & Vanpaemel, 2015).

We estimated the DDM parameters using JAGS 4.3.0 and the R package R2jags (Su & Yajima, 2020). Bias β was always fixed to .5 because we assumed there was no reason to assume that people have an a priori bias for one of the two options. The three other parameters (i.e., drift rate δ, boundary separation α, and non-decision time τ) were estimated for each subject and condition. We ran three chains, each with 101,000 samples and a burn-in period of 1,000 samples. To reduce autocorrelation, the chains were thinned such that every 20th sample was recorded, resulting in 5,000 recorded samples per chain. We assessed chain convergence using the potential scale reduction factor $\hat{R}$ (Gelman & Rubin, 1992). For all parameters, $\hat{R}$ was smaller than 1.004, indicating overall good convergence (Brooks & Gelman, 1998).

For estimates of the DDM parameters, we report means of the group-level posterior distributions and respective 95% highest density intervals (HDI), separately for each condition. The 95% HDI reflects the interval that spans 95% of the distribution such that parameter values outside the interval have lower probability than those inside the interval. To determine whether parameter values differ between conditions, we compared parameter values between two of the relevant conditions (e.g., between two levels of opportunity costs) but within the same level of the other factor (e.g., large value differences). To test the credibility of parameter differences, we computed the 95% HDI of the distribution of differences between the sample values of the chains of each condition. If it does not include 0, the difference is considered credible.

3.4.2.7 Determination of Optimal Boundary Separation

We determined the optimal boundary separation conditional on the choice problems and the opportunity costs in each condition, and conditional on the estimated drift rate δ and non-decision time τ (cf. Evans et al., 2019; Starns & Ratcliff, 2012). We systematically varied the boundary separation α from 0.01 to 6 in steps of 0.01, and computed the expected payoff for each boundary separation and conditional on the factors described above. Within each condition, we identified the boundary separation which yielded the highest payoff—the optimal boundary separation.

3.4.2.8 Experiment 1

Participants made 10 practice choices and 40 main choices between two options. Both opportunity-cost levels and value differences were manipulated between participants. Opportunity costs were set to 0 points (i.e., no costs), 0.5 points, and 1 point per 750 ms. The difference between the options' EVs was either small (difference: 1 point), moderate (10 points), or large (20 points). We collected data of 271 participants (44.3% female, 54.2% male, 1.5% nonbinary, 18–66 years, M_{age} = 29.1, SD_{age} = 9.2, 54.6% had a bachelor's degree or more).

3.4.2.9 Experiment 2

In Experiment 2, opportunity costs were manipulated between participants, using the same levels as in Experiment 1 (i.e., 0 points, 0.5 points, and 1 point per 750 ms). In contrast to the previous study, we varied value differences within participants in blocks with the same value differences used in Experiment 1 (i.e., differences in EVs were 1, 10, and 20). We designed the study so that people were able to learn about the properties of the choices problems without being pointed towards the differences in EV differences. To that end, participants were instructed that there would be three blocks of trials with different types of choice problems but they were not told about the nature of these differences. To differentiate blocks without labeling them, we assigned colors to each block (i.e., green, blue, and red; color assignment and order were randomized for each participant). In each choice problem of the blocks, a colored frame surrounded the choice screen and the color of the block was stated at the top of the screen (for a screenshot, see Figure S2.3 in the Supplemental Materials). To provide participants with the opportunity to learn about the types of choice problems included in each block, in the practice phase, participants completed three blocks each consisting of 20 choice problems. In the following main phase, participants made 45 choices per block in the same block order (maintaining the color-block assignment). The first five choices were practice trials to remind participants of the choice problems of the current block, followed by the 40 consequential main choices. This design ensured that participants had sufficient opportunity to learn about the choice problems of each block. The main choice problems were the same as in Experiment 1, but we added new practice problems due to the increased number of practice trials. We collected data of 92 participants of which two were excluded from data analysis because they stated to be color blind (color blindness could have limited the ability to distinguish between blocks). Of the remaining 90 participants, 46.7% were female and 53.3% were male (18–57 years, M_{age} = 27.7, SD_{age} = 9.0, 53.3% had a bachelor's degree or more).

3.4.2.10 Experiment 3

Experiment 3 was identical to Experiment 2 except for the following differences. First, the three opportunity cost levels were 0 points (i.e., no costs), 0.1 points, and 1 point per 750 ms. Second, differences between the options' EVs were either small (1 point), large (20 points), or very large (60 points). Because adapting the previously used set of choice problems to the very large EV differences led to stochastically dominated options in about half of the problems, we replaced those with new choice problems generated in the same way as for Experiments 1 and 2. Otherwise, the procedure was the same as in Experiment 2. We collected data of 93 participants of which one was excluded because they stated to be color blind. Of the remaining 92 participants, 35.6% were female and 64.4% were male (18–65 years, M_{age} = 26.8, SD_{age} = 8.2, 55.6% had a bachelor's degree or more).

References

Balci, F., Simen, P., Niyogi, R., Saxe, A., Hughes, J. A., Holmes, P., & Cohen, J. D. (2011). Acquisition of decision making criteria: Reward rate ultimately beats accuracy. *Attention, Perception & Psychophysics*, *73*(2), 640–657. https://doi.org/10.3758/s13414-010-0049-7

Bhui, R. (2019). A statistical test for the optimality of deliberative time allocation. *Psychonomic Bulletin & Review*, *26*(3), 855–867. https://doi.org/10.3758/s13423-018-1555-1

Bogacz, R., Hu, P. T., Holmes, P. J., & Cohen, J. D. (2010). Do humans produce the speed-accuracy trade-off that maximizes reward rate? *Quarterly Journal of Experimental Psychology*, *63*(5), 863–891. https://doi.org/10.1080/17470210903091643

Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, *7*(4), 434–455. https://doi.org/10.1080/10618600.1998.10474787

Evans, N. J., Bennett, A. J., & Brown, S. D. (2019). Optimal or not; depends on the task. *Psychonomic Bulletin & Review*, *26*(3), 1027–1034. https://doi.org/10.3758/s13423-018-1536-4

Evans, N. J., & Brown, S. D. (2017). People adopt optimal policies in simple decision-making, after practice and guidance. *Psychonomic Bulletin & Review*, *24*(2), 597–606. https://doi.org/10.3758/s13423-016-1135-1

Fiedler, K., McCaughey, L., Prager, J., Eichberger, J., & Schnell, K. (2021). Speed-accuracy trade-offs in sample-based decisions. *Journal of Experimental Psychology: General*, *150*(6), 1203–1224. https://doi.org/10.1037/xge0000986

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*, 457–472. https://doi.org/http://doi.org/10.1214/ss/1177011136

Hausfeld, J., & Resnjanskij, S. (2018). *Risky decisions and the opportunity cost of time* (Working Paper No. 269). ifo Institute. Munich.

Jarvstad, A., Rushton, S. K., Warren, P. A., & Hahn, U. (2012). Knowing when to move on: Cognitive and perceptual decisions in time. *Psychological Science*, *23*(6), 589–597. https://doi.org/10.1177/0956797611426579

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(33), 13852–13857. https://doi.org/10.1073/pnas.1101328108

Kruschke, J. K., & Vanpaemel, W. (2015). Bayesian estimation in hierarchical models. In J. R. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), *The Oxford handbook of computational and mathematical psychology* (pp. 279–299). Oxford University Press.

Kruschke, J. K. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. Academic Press.

Oud, B., Krajbich, I., Miller, K., Cheong, J. H., Botvinick, M., & Fehr, E. (2016). Irrational time allocation in decision-making. *Proceedings of the Royal Society B*, *283*(1822), Article 20151439. https://doi.org/10.1098/rspb.2015.1439

Payne, J. W., Bettman, J. R., & Luce, M. F. (1996). When time is money: Decision behavior under opportunity-cost time pressure. *Organizational Behavior and Human Decision Processes*, *66*(2), 131–152. https://doi.org/10.1006/obhd.1996.0044

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.

Rahnev, D., & Denison, R. N. (2018). Suboptimality in perceptual decision making. *Behavioral and Brain Sciences*, *41*, e223. https://doi.org/10.1017/S0140525X18000936

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. https://doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, *20*(4), 873–922. https://doi.org/10.1162/neco.2008.12-06-420

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. https://doi.org/10.1016/j.actpsy.2007.05.004

Simen, P., Contreras, D., Buck, C., Hu, P., Holmes, P., & Cohen, J. D. (2009). Reward rate optimization in two-alternative decision making: Empirical tests of theoretical predictions. *Journal of Experimental Psychology: Human Perception and Performance*, *35*(6), 1865–1897. https://doi.org/10.1037/a0016926

Starns, J. J., & Ratcliff, R. (2010). The effects of aging on the speed-accuracy compromise: Boundary optimality in the diffusion model. *Psychology and Aging*, *25*(2), 377–390. https://doi.org/10.1037/a0018022

Starns, J. J., & Ratcliff, R. (2012). Age-related differences in diffusion model boundary optimality with both trial-limited and time-limited tasks. *Psychonomic Bulletin & Review*, *19*(1), 139–145. https://doi.org/10.3758/s13423-011-0189-3

Su, Y.-S., & Yajima, M. (2020). *R2jags: Using R to run "JAGS"* (Version 0.5-7) [Computer software]. https://cran.r-project.org/web/packages/R2jags/R2jags.pdf

Trommershäuser, J., Maloney, L. T., & Landy, M. S. (2008). Decision making, movement planning and statistical decision theory. *Trends in Cognitive Sciences*, *12*(8), 291–297. https://doi.org/10.1016/j.tics.2008.04.010

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory & Cognition*, *32*(7), 1206–1220. https://doi.org/10.3758/BF03196893

Chapter 4:
The Role of Cognitive Effort in Processing Medical Information

Graphical Representations of Medical Information Require More Cognitive Effort than Numbers, but are Preferred

Kevin E. Tiede[1,2] & Wolfgang Gaissmaier[2,3]

[1]Graduate School of Decision Sciences, University of Konstanz
[2]Department of Psychology, University of Konstanz
[3]Centre for the Advanced Study of Collective Behaviour, University of Konstanz

This research was funded by the Committee on Research, University of Konstanz.

Abstract

Graphical representation formats (e.g., icon arrays) have been shown to improve understanding of benefits and risks of treatments compared to numbers. However, less is known about the cognitive effort that is required to process different representation formats. We manipulated time pressure to study how cognitive effort associated with processing numerical, graphical, and inconsistent representations of statistical treatment information and further investigate the role of numeracy and graph literacy in this regard. In a between-participants experiment, 665 participants were provided with the benefits and side effects of six medications and were asked questions about them. First, we manipulated whether the medical information was represented numerically, graphically (i.e., as icon arrays), or in an inconsistent fashion (i.e., numerically for three medications and graphically for the other three). Second, we manipulated whether there was time pressure or not. In an additional intervention condition, participants were asked to translate graphical into numerical information before answering questions. We also assessed numeracy and graph literacy. Results showed that answering knowledge questions with icon arrays (vs. numbers) took longer and was more strongly affected by time pressure. Inconsistent representations led to worse decisions and knowledge, which could be improved through the intervention. The inconsistent condition further revealed a preference towards the graphically presented options. People higher (vs. lower) in numeracy processed quantitative information more efficiently. In sum, graphical representations of statistical information are preferred, but require more cognitive effort than numerical representations. Our results suggest that cognitive effort should be considered more strongly in future research and the design of medical information.

4.1 Introduction

In order to make informed medical decisions, patients have to understand the benefits and risks associated with the medical treatments available, which is often challenging (Gigerenzer et al., 2007; Peters et al., 2007; Reyna et al., 2009). To help patients to comprehend medical information, decision aids have been developed which often present the frequencies of benefits and side effects as graphics such as icon arrays or bar plots (Stacey et al., 2017). A multitude of studies has shown that these graphical presentation formats improve understanding of medical information compared to the presentation of numbers (for reviews, see Garcia-Retamero & Cokely, 2017; Spiegelhalter, 2017; Trevena et al., 2021). However, one aspect that has received little attention so far is how easily graphical and numerical formats can be processed. In this paper, we study how much cognitive effort the processing of icon arrays and numbers requires. In a preregistered experiment, we study cognitive effort in terms of how much time participants need to understand information presented in different formats and how susceptible different formats are to time pressure. Further, we study how people process *inconsistent* representations that mix graphs and numbers, and whether an intervention that asks participants to translate graphically represented information into numbers is helpful in this regard. Finally, we test whether people with higher (vs. lower) numeric and graphical skills also process information more efficiently.

4.1.1 Numerical vs. Graphical Representation

Various studies have demonstrated that people understand medical information better when it is presented as icon arrays than as numbers (for a recent review, see Trevena et al., 2021). However, less attention has been paid to the cognitive processes underlying the effect of presentation format, in particular how easily people process graphical vs. numerical information. One way to capture cognitive effort in decision making and surveys in general is to measure response times (e.g., Bassili & Scott, 1996; Bettman et al., 1990; Cooper-Martin, 1994; Fazio, 1990), with longer response times indicating more cognitive effort (McCaffery et al., 2012; Oudhoff & Timmermans, 2015; Price et al., 2008; Zikmund-Fisher et al., 2010). Previous studies investigating graphical and numerical risk formats have shown that people take more time to respond to questions when they work with graphical formats than with numbers (Garcia-Retamero et al., 2016; Smerecnik et al., 2010; but see Brewer et al., 2012). In the study by Garcia-Retamero et al. (2016), surgeons took more time to deliberate with icon arrays than with numbers, so that the authors concluded that icon arrays improve comprehension partly because they increase the time people take to deliberate. However, the correlational design of this and other studies could not test why participants deliberated longer. For instance, participants could have merely *taken* more time when provided with icon arrays, but perhaps they rather *needed* more time because they are harder to process. Our study aims to disentangle these accounts by experimentally studying understanding of information when time is limited. If one format requires more cognitive effort than another, it should not only lead to longer response times, but it should also to worse decisions and understanding under time pressure.

Therefore, our study aimed to provide answers to the following exploratory research questions (RQ) regarding the processing of graphically and numerically represented information, one of which was preregistered:

RQ1: Do response times differ when information is presented numerically vs. graphically? (not preregistered)

RQ2: Does decision accuracy differ when information is presented numerically vs. graphically? (preregistered)

RQ3: Does time pressure harm decisions more strongly when information is presented graphically than numerically? (not preregistered)

4.1.2 Consistent vs. Inconsistent Representation

Moreover, our goal is to study how people process inconsistently represented information, that is when information is represented partly numerically and partly graphically. Studying inconsistent representations can provide various insights into the processing of information. First, it can be learned how people internally represent numerically and graphically represented information when provided with both types of representation. If they internally represent the information similarly (e.g., solely as numeric information), decision accuracy and knowledge should be comparable to when information which is fully represented either numerically or graphically. However, when the internal representation of information differs, decision accuracy and knowledge should be worse with inconsistent (vs. consistent) representation. Second, we investigate whether processing inconsistently represented information requires more cognitive effort than processing fully numerical or graphical representations. For that purpose, we study how long people need to process inconsistently represented information and the degree to which time pressure harms decision accuracy in comparison to consistently represented information. Third, we test whether people deal with inconsistent information representation by translating the information of one representation into another before comparing options and whether prompting people to perform this translation improves decisions. To that end, the study includes an experimental condition in which people are asked to translate the graphically represented information into numbers before answering the questions about the information. If people process inconsistent information by translating one representation into another, there should be no difference between the condition with and without this intervention. However, if people do not perform this translation although they are capable of it, decision accuracy should be higher with an intervention than without and accuracy of translations should be high.

Furthermore, we study whether the format in which an option is presented affects not only the processing but also the evaluation of information. People have been shown to prefer graphical over numerical presentation formats (Nayak et al., 2016). Further, people allocate more attention to graphical than numerical formats (Smerecnik et al., 2010) and more attention to an option, in turn, has been shown to increase the likelihood of choosing it (Krajbich et al., 2010; Krajbich & Rangel, 2011). Therefore, we test whether people exhibit a preference for the graphically represented option in the inconsistent conditions by examining the format of the chosen treatments controlling for decision accuracy.

We preregistered the following six confirmatory hypotheses with regard to the processing of inconsistently represented information:

H1: When there is no time limit, people take more time to make a decision with inconsistently presented information than when all information is presented numerically.

H2: When there is time pressure, people will choose the superior option less often than when there is no time pressure.

H3: When treatment options are presented inconsistently, people will choose the superior option less often than when they are presented consistently (i.e., fully numerically or graphically).

H4: When treatment options are presented inconsistently, time pressure (vs. no time pressure) will decrease choice accuracy more strongly with inconsistent information than with consistent information.

H5: An intervention which prompts people to translate graphical into numerical information in the inconsistent condition will improve decisions compared to the inconsistent condition without an intervention.

H6: When choosing between treatments which are presented differently between treatments in the inconsistent condition, people have a preference for the graphically (vs. numerically) represented option.

4.1.3 Numeracy and Graph Literacy

Besides the presentation format, people's cognitive abilities affect how well they understand information. People higher (vs. lower) in numeracy, the ability to process and understand numerical information (Peters, 2012; Peters et al., 2006), have been found to understand medical information better and to deliberate longer when working with medical information (Garcia-Retamero & Cokely, 2017; Peters, 2020). However, it is less clear whether numeracy is related to superior decision making through more intensive deliberation or numeracy is also related to a more efficient processing of information (Hess et al., 2011). To examine whether people higher (vs. lower) in numeracy are also more efficient when working with numbers and/or graphs, we test whether their decision accuracy and knowledge is less affected by time pressure. Furthermore, numeracy has also been shown to affect how people process icon arrays. Specifically, people lower in numeracy rather process the arrays more holistically, whereas people higher in numeracy tend to count icons (Kreuzmair et al., 2016, 2017). Due to the better comparability of counted icons with numbers, people higher (vs. lower) in numeracy should benefit less from the intervention which consists of translating graphical into numerical information. Thus, we test whether the effect of the intervention on decision accuracy is moderated by numeracy.

Finally, people higher (vs. lower) graph literacy, the ability to understand graphically presented information, have been shown to better comprehend icon arrays and are better at identifying task-relevant information in graphs (Galesic & Garcia-Retamero, 2011; Okan et al., 2016). However, analogously to numeracy, it is also unclear whether graph literacy is related to the efficiency of processing graphically represented information. Therefore, we further test whether decisions of people higher (vs. lower) in graph literacy are less affected by time pressure.

Thus, we aim to find answers to the following exploratory research questions, one of which was preregistered:

RQ4: Is decision accuracy of people higher (vs. lower) in numeracy and/or graph literacy less negatively affected by time pressure? (preregistered)

RQ5: Does numeracy moderate the effect of intervention on decision accuracy so that the intervention improves accuracy less strongly for people higher (vs. lower) in numeracy (not preregistered)?

4.1.4 The Present Study

In sum, the present research examines how people process medical information when the information about treatment options is represented as numbers, icon arrays, or both and how much cognitive effort the processing of this information requires. For this purpose, we provided participants with the relative frequencies of benefits and side effects of six treatments presented in different ways. Then, we assessed decision accuracy by asking participants to choose a treatment they would prefer as a patient, with two of the six treatments being superior. Subsequently, we assessed knowledge by asking participants to answer a variety of questions about the medications. We further manipulated whether there was a time limit to answer the questions or not. Finally, we assessed numeracy and graph literacy.

We preregistered the study, two of the above-mentioned exploratory RQs, and all stated confirmatory hypotheses as well as their analyses (https://osf.io/h37ej/?view_only=296db7b2a9a443869b4b68d160a89e02). All preregistered RQs and hypotheses focused on response times and decisions as outcome variables, yet we studied all RQs and hypotheses regarding decisions also with knowledge as outcome variable.

4.2 Methods

The study was approved by the ethics committee of the University of Konstanz, Germany.

4.2.1 Design

All participants were provided with information on six hypothetical medications to treat Multiple Sclerosis (MS; see Table 4.1). In particular, the information presented how many of 100 people experienced benefits and side effects of each treatment. The relative frequencies were constructed in a way that for each of two triplets of medications, one medication was dominant (i.e., equal or more frequent benefits and equal or less frequent side effects), resulting in two dominant options across all six medications. A medication of one triplet did not dominate the medications of the other triplet. While the medical information was the same for all participants, the way the information was presented

Table 4.1: Medical data used in the study.

	Benefits	Side effects
Medication 1	67 out of 100	31 out of 100
Medication 2	67 out of 100	37 out of 100
Medication 3	63 out of 100	34 out of 100
Medication 4	46 out of 100	21 out of 100
Medication 5	41 out of 100	21 out of 100
Medication 6	43 out of 100	25 out of 100

Note. Allocation and labels of medications (i.e., “Medication A” etc.) was randomized across participants. Medication 1 dominates Medications 2 and 3 (i.e., has equal/more benefits and equal/less side effects) and Medication 4 dominates Medications 5 and 6.

differed between conditions. In the *numerical* conditions, relative frequencies were presented as numbers (i.e., “x out of 100”; see upper row of Figure 4.1 or Figure S3.1 in the Supplemental Materials). In the *graphical* conditions, relative frequencies were presented as icon arrays (see lower row of Figure 4.1 or Figure S3.2 in the Supplemental Materials). In the *inconsistent* conditions, information on three medications was presented as numbers, whereas the information on the other three medications was presented as icon arrays (for a screenshot, see Figure 4.1; placement of numbers in the upper or lower row was randomized across participants). Further, we manipulated between participants whether there was time pressure or not. In the *time-pressure* conditions, participants had to answer each question within a time limit. Because a pilot study showed that response times differed systematically between question types, the time limit ranged from 15 to 30 seconds (see Table 4.2; the pilot study is described in detail in the Supplemental Materials). These time limits reflected the time in which about half of participants answered the questions without a time limit in a pilot study. The allowed time for each question was announced before each question page and on the question page, the remaining time was presented next to the question (for screenshots, see Supplemental Materials). When the time was up, the study automatically proceeded to the next page. In the *no-time-pressure* conditions, there was no time limit. In addition to these two experimental factors, there was an additional *intervention* condition. In that

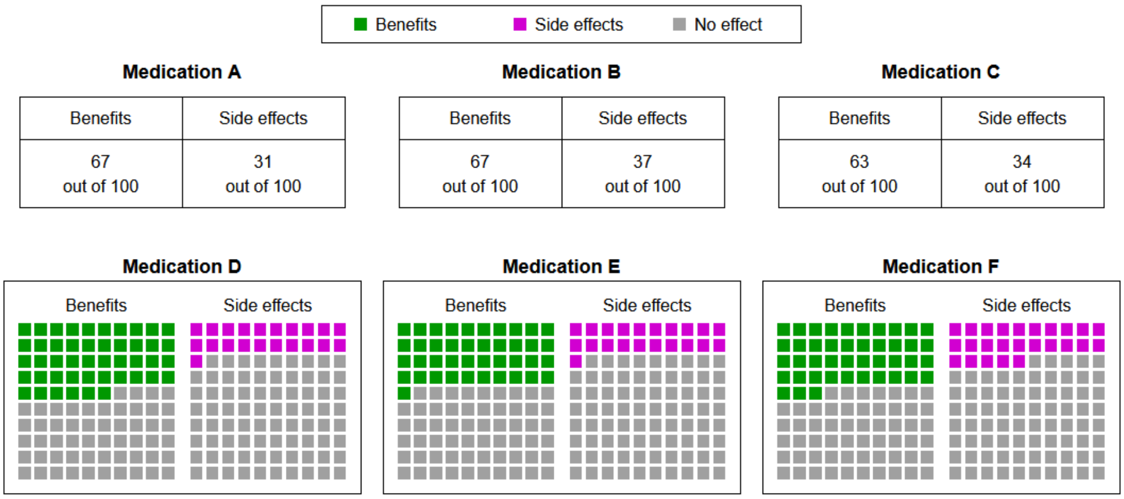

Figure 4.1: Presented medical information as presented in the inconsistent conditions. In the time-pressure conditions, a countdown was placed in the lower-right corner. Whereas the placement of the medications was randomized across participants, in this example Medication A dominates B and C, while Medication D dominates E and F.

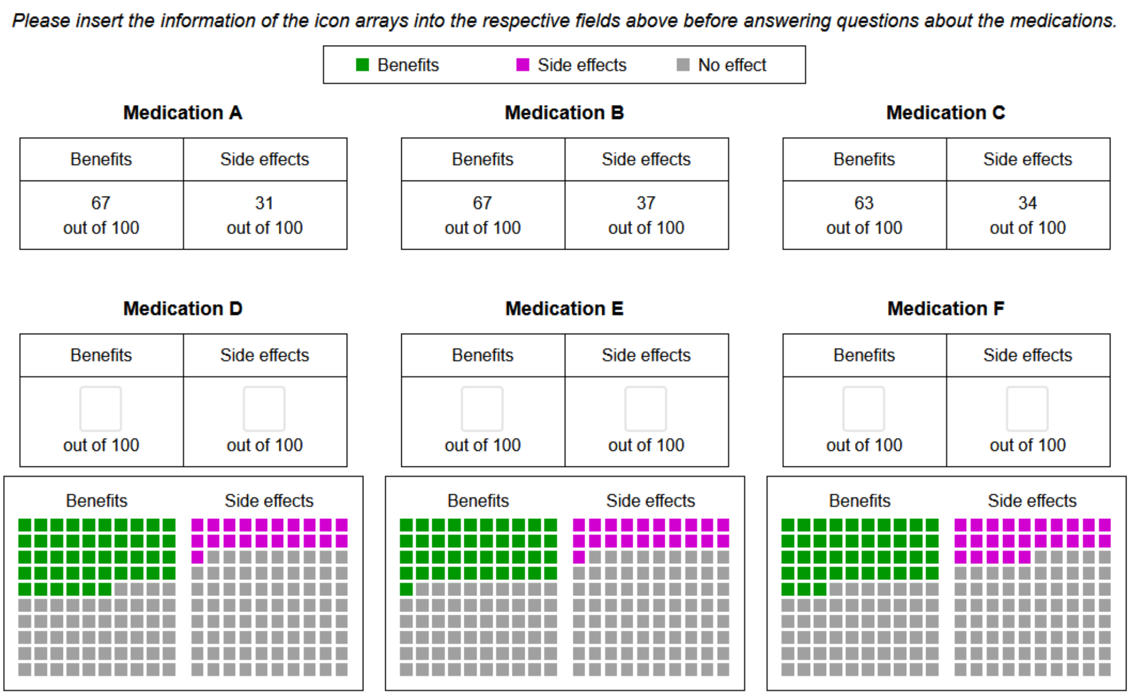

Figure 4.2: Screenshot of the intervention condition. Before answering questions, participants were asked to read off the graphical information and to fill in the frequencies into the respective fields.

condition, there was no time pressure and participants received the same information as in the inconsistent condition, but before answering the questions they were asked to read-off the graphically presented information and insert the respective numeric frequencies into fields below or above the icon arrays (see Figure 4.2). Subsequently, participants were provided with both the original information and their numerical entries when answering the same questions as in the other conditions.

In sum, we implemented a 3 (format: numerical vs. graphical vs. inconsistent) x 2 (time pressure: yes vs. no) between-subjects design with an additional intervention condition. The experimental factors were independent variables, whereas decision accuracy, knowledge, and response times were dependent variables.

4.2.2 Procedure

After providing informed consent[3], participants were randomly assigned to one of the seven conditions. Afterwards, they were instructed that they would be provided with information on the benefits and side effects of six hypothetical treatments to treat Multiple Sclerosis (MS). Then, they were presented with the information on the six medications and asked which medication they would choose if diagnosed with MS. After that decision, participants were asked the eight knowledge questions in randomized order, with the medical information always visible. Subsequently, participants completed measures on numeracy and graph literacy and provided demographic information. After being asked about their seriousness of participation, participants were debriefed.

4.2.3 Measures

A list of all decision and knowledge items can be found in Table 4.2.

4.2.3.1 Decision

After being instructed to imagine being diagnosed with MS in the instructions, in the first question participants were asked to choose the treatments which they preferred: “Considering both the benefits and side effects, which of the medications would you prefer?” Participants could choose one of the six medications. The decision was counted as correct if one of the two dominant treatment options was chosen. If there was no decision submitted due to exceedance of the time limit in the time-pressure conditions, the answer was regarded as incorrect.

[3] Following the informed consent, participants also filled out questionnaires on subjective numeracy (i.e., numeric confidence and numeric preferences) and subjective graph literacy (i.e., graph-related confidence) which were not included in the main analysis.

Table 4.2: Items used in this study and the respective time limits in the time-pressure conditions.

Question Type	Question	Time limit
Decision	Considering both the benefits and side effects, which of the medications would you prefer?	30 sec
Gist knowledge	With which medication did people experience benefits most often?	15 sec
Gist knowledge	With which medication did people experience side effects most often?	15 sec
Verbatim knowledge (reading-off)	If 100 people take Medication E, how many of them will experience benefits?	15 sec
Verbatim knowledge (reading-off)	If 100 people take Medication C, how many of them will experience side effects?	15 sec
Verbatim knowledge (computing-differences)	If 100 people take Medication [A/B]*, how many more of them will experience benefits compared to Medication [A/B]?	25 sec
Verbatim knowledge (computing-differences)	If 100 people take Medication [D/F]*, how many more of them will experience side effects compared to Medication [D/F]?	25 sec
Verbatim knowledge (computing-differences)	If 100 people take Medication [C/D]*, how many more of them will experience benefits compared to Medication [C/D]?	25 sec
Verbatim knowledge (computing-differences)	If 100 people take Medication [A/E]*, how many more of them will experience side effects compared to Medication [A/E]?	25 sec

Note. *In the questions regarding verbatim knowledge (computing-differences), the medication which had the higher benefits or side effects was stated at the first position and the other medication at the second position.

4.2.3.2 Knowledge

We assessed knowledge using eight items which asked about *gist knowledge* (i.e., understanding of the essential information; Reyna, 2008) and *verbatim knowledge* (i.e., precise quantitative knowledge). We measured gist knowledge using two items which required the comparison of all six treatment to identify the medication with the least frequent benefits or the most frequent side effects (e.g., “Which medication did people experience benefits least often with?”). We measured verbatim knowledge using two items which asked participants to read off information about benefits and side effects (e.g., “If 100 people take Medication E, how many of them will experience benefits?”) and four items which asked participants to compute the differences in benefits or side effects between two treatments (e.g., “If 100 people take Medication F, how many more of them will experience side effects compared to Medication D?”). Two of these four items asked about comparisons between medications within the same row (i.e., the same format in the inconsistent conditions) and the other items asked questions about medications in different rows (i.e., different formats in the inconsistent conditions). All items always referred to medications at the same location across participants (e.g., “Medication C”) but the allocation of medications was randomized, so correct answers differed between participants. If there was no answer submitted to a question due to exceedance of the time limit in the time-pressure conditions, the answer was regarded as incorrect. The knowledge scores represent the proportion of correct answer across all eight items.

4.2.3.3 Numeracy

Numeracy was measured using a combination of the non-adaptive version of the four-item Berlin Numeracy Test (Cokely et al., 2012) and the three-item measure by Schwartz et al. (1997). This seven-item measure is recommended for general population online samples (Cokely et al., 2012). The numeracy score represents the sum of all correct answers.

4.2.3.4 Graph Literacy

Graph literacy was measured using the Short Graph Literacy Scale (Okan et al., 2019). It consists of four items which measures the understanding of graphically presented medical information. The graph literacy score represents the sum of all correct answers.

4.2.4 Participants

Participants were recruited via Prolific Academic. To participate, they had to be residing in the US, speak English as their first language, and had to have an approval rate for study participation of at least 95%. As compensation, participants received £1.50 as a flat fee and a performance-contingent bonus of on average £0.80 (*SD* = £0.22). Based on a power analysis using G*Power (Faul et al., 2009), our study required 70 participants per condition to detect a small-to-medium-sized effect ($\alpha = .05$, $1\text{-}\beta = .90$, $f = .175$). Because of the randomized allocation of treatment positions between participants, in the inconsistent conditions the representation formats of the two dominant options differed between participants (i.e., both dominant options were represented either numerically or graphically, or one was represented numerically and the other graphically). To obtain the statistical power to test whether the format of the dominant options affected decisions within each inconsistent condition, we aimed to oversample the inconsistent (vs. consistent) conditions by a ratio of 3:2, yielding a targeted group size of 105 for the inconsistent conditions. Anticipating a participant exclusion of about 15%, we recruited

704 participants. As preregistered, we excluded 32 participants who failed the attention check, five participants who stated that they did not participate seriously, one participant who repeatedly gave unreasonable answers in the numeracy questionnaire, and one participant who stated in the comments that they noticed that they misunderstood the task. In the remaining sample ($N = 665$), 50.5% were females (0.9% stated other gender), age was on average 37.5 years ($SD = 13.1$, range = 18–81), and 66.2% had at least a bachelor's degree. Mean numeracy was 3.6 ($SD = 1.8$) and mean graph literacy was 2.5 ($SD = 1.0$).

4.3 Results

The data and analysis scripts are openly available at https://osf.io/b5aqk/?view_only=3cc241ec56e14070995c9ea2e6488732. In all analyses, numeracy and graph literacy (both mean-centered) were included as predictors. Unless stated otherwise, results were similar when we excluded numeracy and graph literacy as predictors[4].

4.3.1 Numerical vs. Graphical Representation

First, we tested whether response times in decisions and knowledge questions differed between the graphical and the numerical conditions (RQ1). To test this, we conducted a linear regression with log-transformed[5] response times as outcome variable and format (dummy-coded as 0 = numerical, 1 = graphical), numeracy, graph literacy, and their interactions as predictors, using the data of the conditions without time pressure only. Response times are illustrated in Figure 4.3. When making decisions, people took longer to decide with icon arrays (vs. numbers), but this difference was only significant when we did not control for numeracy and graph literacy (with abilities: $b = 0.18$, $p = .135$; without abilities: $b = 0.25$, $p = .020$). When answering knowledge questions, response times were longer when information was presented as icon arrays rather than as numbers ($b = 0.43$, $p < .001$). There were no significant effects of numeracy and graph literacy on response times in decisions and knowledge.

Next, we tested whether decision accuracy differs between the numeric and the graphical conditions (RQ2) and whether time pressure harms decision accuracy more strongly with graphically than numerically represented information (RQ3). Decision

[4] Results were also similar when we added subjective numeracy and graph literacy as covariates.
[5] Because response-time distributions tend to be skewed, we log-transformed response times for analysis. However, for an easier interpretation, response times presented in Figure 4.3 show non-transformed response times.

accuracy and knowledge scores are illustrated in Figure 4.4. To analyze decision accuracy, we conducted a logistic regression with correct answer as outcome variable and time pressure (dummy-coded as 0 = no time pressure, 1 = time pressure) and format (dummy-coded as 0 = numerical, 1 = graphical), numeracy, graph literacy, and their interactions as predictors. Decision accuracy did not differ depending on time pressure ($b = -1.16$, $p = .200$) or format ($b = -0.96$, $p = .295$), nor on their interaction ($b = 0.31$, $p = .772$). Numeracy was positively related to accuracy ($b = 1.02$, $p = .011$), but less so in the graphical condition (interaction: $b = -1.19$, $p = .011$). There were no other significant main effects or interactions of numeracy or graph literacy.

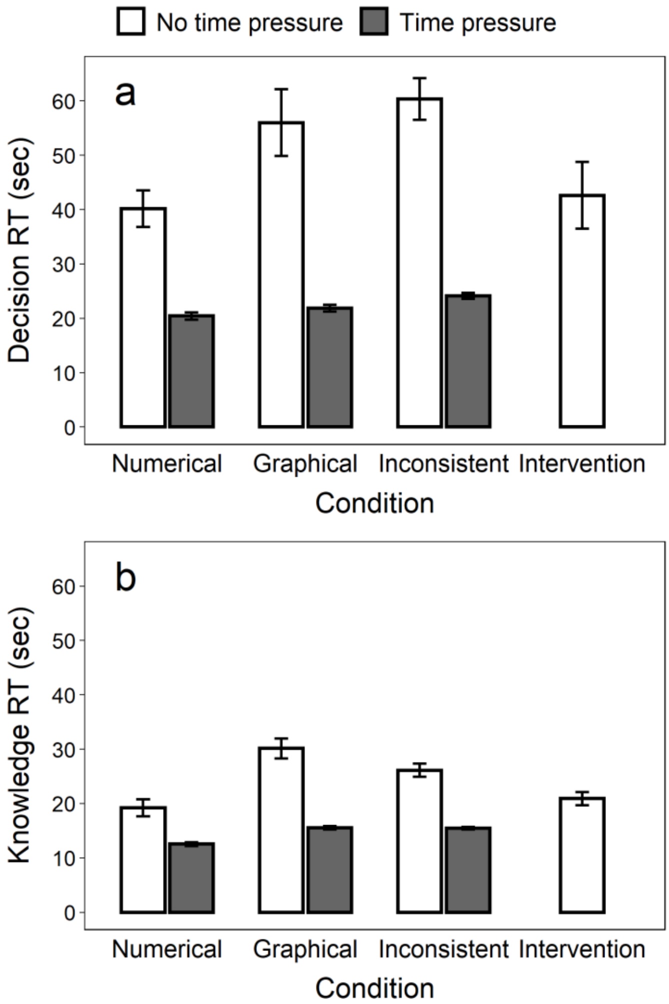

Figure 4.3: Response times (RT) in the decision (a) and averaged across knowledge questions (b). Error bars represent one standard error of the mean. In the time-pressure conditions, response time was limited (decision: 30 seconds; knowledge: 15 seconds for four items, 25 seconds for other four items). Response times in the intervention condition refer to the time for answering questions, without the intervention.

To analyze knowledge, we repeated the analysis, but used a linear regression with knowledge score as outcome variable. Knowledge was lower when there was time pressure (vs. no time pressure; $b = -0.12$, $p = .004$) and when information was presented graphically (vs. numerically; $b = -0.11$, $p = .007$). Further, there was a significant interaction between the two predictors, suggesting that time pressure decreased knowledge more strongly when information was presented graphically (vs. numerically; $b = -0.20$, $p < .001$). There were no main effects of numeracy ($b = 0.03$, $p = .120$) or graph literacy ($b = 0.02$, $p = .576$) on knowledge. However, there was a significant interaction of time pressure and numeracy ($b = 0.06$, $p = .012$), indicating that higher (vs. lower) numeracy was more beneficial when there was time pressure.

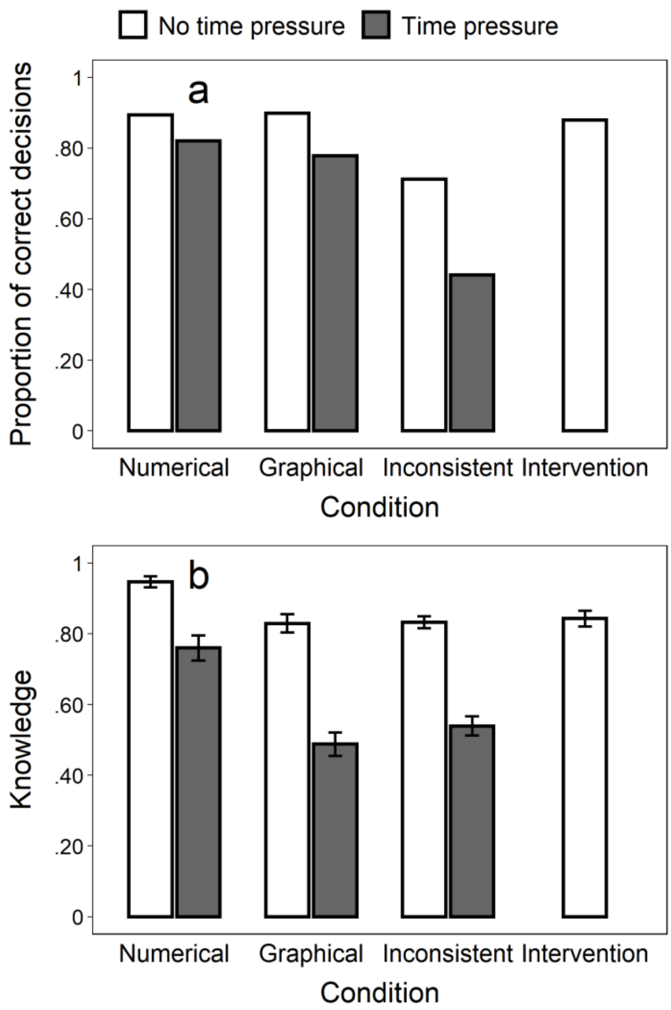

Figure 4.4: Decision accuracy (a) and knowledge (b) across conditions. Error bars represent one standard error of the mean (no error bars are displayed for decisions because the bars represent proportions).

4.3.2 Consistent vs. Inconsistent Representation

Next, we tested whether people take more time to make a decision with inconsistently presented information than when all information is presented numerically (H1). To test this, we conducted the same analysis for the comparison of numerical vs. graphical representation, but comparing the inconsistent condition with the numerical and graphical condition with two dummy variables for format (dummy 1: 0 = inconsistent, 1 = numerical, dummy 2: 0 = inconsistent, 1 = graphical). Thus, the inconsistent condition was the reference condition in this analysis. Response times are illustrated in Figure 4.3. When information was presented inconsistently, response times were longer for decisions ($b = -0.44$, $p < .001$) and knowledge ($b = -0.31$, $p < .001$) than when information was presented purely numerically, supporting H1. In the inconsistent condition, decisions were also made slower ($b = -0.26$, $p = .014$) than in the graphical condition, but answers to knowledge questions were given faster ($b = 0.12$, $p = .046$). Whereas there were no effects of numeracy or graph literacy on response times in decisions, people higher (vs. lower) in numeracy, but not graph literacy, responded faster to the knowledge questions ($b = -0.08$, $p < .001$).

Next, we tested whether time pressure harms decision accuracy (H2), whether inconsistent information representation leads to less accurate decisions than consistent representation (H3), and whether the effect of time pressure is stronger in the inconsistent (vs. consistent) conditions (H4). Further, we tested whether decisions of people higher (vs. lower) numeracy and graph literacy are less affected by time pressure (RQ4). For that reason, we conducted the same analysis as for the comparison between graphical vs. numerical representation, but with two format dummy variables (dummy 1: 0 = inconsistent, 1 = numerical, dummy 2: 0 = inconsistent, 1 = graphical). Decision accuracy and knowledge scores are illustrated in Figure 4.4.

Decisions were less accurate when there was time pressure (vs. no time pressure; $b = -1.18$, $p < .001$), supporting H2. Further, as expected, choices were less accurate when options were presented inconsistently than when all information was numerical ($b = 2.42$, $p = .003$) or graphical ($b = 1.46$, $p = .006$), consistent with H3. However, contrary to H4, time pressure did not compromise accuracy more strongly in inconsistent than in purely numerical ($b = 0.02$, $p = .983$) or graphical presentations ($b = 0.33$, $p = .618$). Regarding cognitive abilities, graph literacy ($b = 0.48$, $p = .044$), but not numeracy ($b = 0.19$, $p = .169$) was positively associated with decision accuracy. However, in the numerical condition, numeracy was more strongly associated with accuracy than in the inconsistent condition (interaction: $b = 0.83$, $p = .049$). No other interactions with numeracy or graph literacy were significant.

Knowledge was lower when there was time pressure (vs. no time pressure; $b = -0.30$, $p < .001$). When information was represented inconsistently, knowledge was lower than when represented numerically ($b = 0.11$, $p = .002$), but not when represented graphically ($b = 0.00$, $p = .977$). The superiority of numerical over inconsistent representation was even stronger when there was time pressure (vs. no time pressure; interaction: $b = 0.18$, $p < .001$). Both numeracy ($b = 0.03$, $p = .043$) and graph literacy ($b = 0.05$, $p = .017$) were positively related to knowledge and the association of numeracy and knowledge was even stronger when there was time pressure (interaction: $b = 0.05$, $p = .004$).

4.3.3 Intervention

Next, we tested whether decisions with inconsistent representation would be more accurate with an intervention than without (H5) and whether numeracy would moderate the effect of intervention on decision accuracy (RQ5). Overall, participants in the intervention condition correctly translated 90.7% ($SD = 24.6$) of the graphically presented information into numbers. To test the benefit of the intervention, we conducted a logistic regression with choice accuracy as outcome variable and intervention (dummy-coded as 0 = no intervention, 1 = intervention), numeracy, graph literacy, and their interactions as predictors. We analyzed the data of the inconsistent-no-time-pressure condition and intervention condition only. As expected, choices were more accurate with the intervention than without ($b = 1.87$, $p < .001$), supporting H5. The effect of intervention did not depend on numeracy (interaction: $b = 0.59$, $p = .061$) or graph literacy (interaction: $b = -0.42$, $p = .522$). When we compared the decision accuracy of the intervention condition to that of the numerical and graphical conditions without time pressure, decision accuracy did not differ from that in the numerical ($b = 0.55$, $p = .548$) and graphical condition ($b = -0.41$, $p = .553$).

4.3.4 Format Preferences

Finally, we tested whether there exists a preference for the graphically presented options when some options are presented numerically and some graphically (H6). For this purpose, we analyzed choices of the inconsistent conditions and controlled for decision accuracy. We conducted a logistic regression with choice for a graphically presented option as the outcome variable and correct choice (dummy-coded as 0 = incorrect choice, 1 = correct choice), numeracy, graph literacy, and their interactions as predictors. Independently of the correctness of the choices, participants exhibited a preference for the graphically represented options. This was indicated by an intercept which was significantly different from 0 (intercept = 0.58, $p = .015$) which translates into a 64.0% probability to choose the graphically represented option when controlling for the other predictors. Thus, H6 was supported.

4.4 Discussion

Graphical risk formats have been shown to improve understanding of medical information compared to numerical formats (Spiegelhalter, 2017; Trevena et al., 2021). Our research aimed to study cognitive effort required to process different representation formats and how people process medical information when it is represented inconsistently. In our experiment, participants were provided with information about the benefits and side effects of hypothetical medications and were asked to choose a preferred medication and to answer knowledge questions about them. Relative frequencies were either presented as numbers, as icon arrays, or inconsistently (i.e., numbers for some medications and icon arrays for others). Further, we manipulated whether there was time pressure or not. Our results showed that graphical formats require more cognitive effort than numerical formats when answering knowledge questions. Furthermore, inconsistent representation led to worse decisions than when information was presented in the same format. Participants were able to translate information from one representation into another, but they did not seem to do so when not explicitly asked to. Moreover, when medical information was presented inconsistently, participants exhibited a preference for the graphically represented options. Finally, higher numeracy was associated with a higher efficiency to process information when knowledge was relevant.

In line with previous findings (Garcia-Retamero et al., 2016; Smerecnik et al., 2010), graphical formats led to longer response times than numbers when participants answered knowledge questions. Our time-pressure manipulation demonstrated that this is at least partly due to icon arrays requiring more cognitive effort than numbers, although we found no differences when making decisions. Together with research showing that icon arrays are beneficial for understanding the essential (or gist) knowledge of information (Trevena at al., 2021), our results suggest that icon arrays may be a good way to communicate medical information when the ordinal comparison of information is required. However, when knowledge is relevant, graphical formats may be less beneficial due to more cognitive effort required to process information.

When information was represented inconsistently, decisions took longer and were substantially worse than when all options were presented in the same format. This suggests that when dealing with inconsistent representation, graphs and numbers are processed in different ways and as a result, the limited comparability harms understanding. However, time pressure did not harm decision accuracy more than in the numerical or graphical condition. Thus, our expectation that inconsistent representations require more cognitive effort than consistent ones was not supported by the time-pressure manipulation, although participants took considerably longer to respond with inconsistent (vs. consistent) representation when there was no time pressure. Further, when participants were asked to translate information from the icon arrays into numbers, the translations were mostly correct, and following decisions were better than without this intervention. This implies that people succeed in translating one representation into another, but that they do not so by default when confronted with inconsistently represented information. Finally, as participants exhibit a preference for the graphically represented options, our study showed that the representation of information does not only affect comprehension of information but can also change treatment preferences.

While numeracy was partially related to decision accuracy and knowledge, we found that knowledge (but not decisions) by people higher (vs. lower) in numeracy was less affected by time pressure. This suggests that higher (vs. lower) numeracy not only improves the understanding and use of numbers (Garcia-Retamero et al., 2019: Peters & Bjalkebring, 2015), but also allows people to process information with less effort. However, the tendency of more numerate people to count icons (Kreuzmair et al., 2016, 2017) did not affect the benefit of the intervention, as decisions of more and less numerate people improved similarly with an intervention compared to without an intervention. Finally, graph literacy partially improved decisions and knowledge with inconsistent representation, but it was not associated with more efficient processing of graphical information.

4.5 Limitations

Limitations of our study have to be considered. First, our study was conducted with a sample from the general population and used hypothetical medical data. Possibly, affected patients process medical information differently than non-patient participants.

However, as our goal was to study the general processing of graphical and numerical information, we believe that our approach allows for a more general conclusions about the effect of representation format on required cognitive effort. Second, although the time limits used in this study were chosen based on results of our pilot study, we acknowledge that they were somewhat arbitrary and that different time limits could have led to other results and thus conclusions.

4.6 Conclusion

Studying the processes which underlie the effects of presentation format on medical decision making allows for gathering new and important insights into the mechanisms underlying risk communication and perception. Our findings emphasize the value of studying risk communication beyond the examination of understanding and choices and highlight the importance of considering features of the environment as well the goals of risk communication when studying risk formats (Tiede et al., 2020). As a practical implication, our study suggests that when choosing how to present information, comprehension and cognitive effort may have to be traded off. Especially when the environment reduces the availability of cognitive resources (e.g., through time pressure or noise) or patients generally have lower cognitive skills, numbers could be more beneficial if knowledge is important. In conclusion, we believe that studying how patients process medical information helps to better understand how, why, and under which conditions different presentation formats improve medical decision making.

References

Bassili, J. N., & Scott, B. S. (1996). Response latency as a signal to question problems in survey research. *Public Opinion Quarterly, 60*(3), 390–399. https://doi.org/10.1086/297760

Bettman, J. R., Johnson, E. J., & Payne, J. W. (1990). A componential analysis of cognitive effort in choice. *Organizational Behavior and Human Decision Processes, 45*(1), 111–139. https://doi.org/10.1016/0749-5978(90)90007-V

Brewer, N. T., Gilkey, M. B., Lillie, S. E., Hesse, B. W. & Sheridan, S. L. (2012). Tables or bar graphs? Presenting test results in electronic medical records. *Medical Decision Making, 32*(4), 545–553. https://doi.org/10.1177/0272989X12441395

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., & Garcia-Retamero, R. (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making, 7*, 25–47.

Cooper-Martin, E. (1994). Measures of cognitive effort. *Marketing Letters, 5*(1), 43–56. https://doi.org/10.1007/BF00993957

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fazio, R. H. (1990). A practical guide to the use of response latency in social psychological research. In C. Hendrick & M. S. Clark (Eds.), *Research methods in personality and social research* (pp. 74–97). Sage.

Galesic, M., & Garcia-Retamero, R. (2011). Graph literacy: A cross-cultural comparison. *Medical Decision Making, 31*, 444–457. https://doi.org/10.1177/0272989X10373805

Garcia-Retamero, R., & Cokely, E. T. (2017). Designing visual aids that promote risk literacy: A systematic review of health research and evidence-based design heuristics. *Human Factors, 59*, 582–627. https://doi.org/10.1177/0018720817690634

Garcia-Retamero, R., Cokely, E. T., Wicki, B., & Joeris, A. (2016). Improving risk literacy in surgeons. *Patient Education and Counseling, 99*(7), 1156-1161. https://doi.org/10.1016/j.pec.2016.01.013

Garcia-Retamero, R., Sobkow, A., Petrova, D., Garrido, D., & Traczyk, J. (2019). Numeracy and risk literacy: What have we learned so far? *The Spanish Journal of Psychology, 22*, E10. https://doi.org/10.1017/sjp.2019.16

Gigerenzer, G., Gaissmaier, W., Kurz-Milcke, E., Schwartz, L. M., & Woloshin, S. (2007). Helping doctors and patients make sense of health statistics. *Psychological Science in the Public Interest, 8*, 53–96. https://doi.org/10.1111/j.1539-6053.2008.00033.x

Hess, R., Visschers, V. H. M., Siegrist, M., & Keller, C. (2011). How do people perceive graphical risk communication? The role of subjective numeracy. *Journal of Risk Research, 14*(1), 47–61. https://doi.org/10.1080/13669877.2010.488745

McCaffery, K. J., Dixon, A., Hayen, A., Jansen, J., Smith, S., & Simpson, J. M. (2012). The influence of graphic display format on the interpretations of quantitative risk information among adults with lower education and literacy: A randomized experimental study. *Medical Decision Making, 32*(4), 532–544. https://doi.org/10.1177/0272989X11424926

Nayak, J. G., Hartzler, A. L., Macleod, L. C., Izard, J. P., Dalkin, B. M., & Gore, J. L. (2016). Relevance of graph literacy in the development of patient-centered communication tools. *Patient Education and Counseling, 99*, 448–454. http://dx.doi.org/10.1016/j.pec.2015.09.009

Okan, Y., Galesic, M., & Garcia-Retamero, R. (2016). How people with low and high graph literacy process health graphs: Evidence from eye-tracking. *Journal of Behavioral Decision Making, 29*, 271–294. https://doi.org/10.1002/bdm.1891

Okan, Y., Janssen, E., Galesic, M., & Waters, E. A. (2019). Using the short graph literacy scale to predict precursors of health behavior change. *Medical Decision Making. 39*(3), 183–195. https://doi.org/10.1177/0272989X19829728

Oudhoff, J. P., & Timmermans, D. R. M. (2015). The effect of different graphical and numerical likelihood formats on perception of likelihood and choice. *Medical Decision Making, 35*(4), 487–500. https://doi.org/10.1177/0272989X15576487

Peters, E. (2012). Beyond comprehension: The role of numeracy in judgments and decisions. *Current Directions in Psychological Science*, *21*(1), 31–35. https://doi.org/10.1177/0963721411429960

Peters, E. (2020). *Innumeracy in the wild: Misunderstanding and misusing numbers*. Oxford University Press.

Peters, E., & Bjalkebring, P. (2015). Multiple numeric competencies: When a number is not just a number. *Journal of Personality and Social Psychology*, *108*, 802–822. https://doi.org/10.1037/pspp0000019

Peters, E., Hibbard, J., Slovic, P., & Dieckmann, N. (2007). Numeracy skill and the communication, comprehension, and use of risk-benefit information. *Health Affairs*, *26*, 741–748. https://doi.org/10.1377/hlthaff.26.3.741

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science*, *17*, 407–413. https://doi.org/10.1111/j.1467-9280.2006.01720.x

Reyna, V. F. (2008). A theory of medical decision making and health: Fuzzy-trace theory. *Medical Decision Making*, *28*, 829–833. https://doi.org/10.1177/0272989X08327066

Reyna, V. F., Nelson, W. L., Han, P. K., & Dieckmann, N. F. (2009). How numeracy influences risk comprehension and medical decision making. *Psychological Bulletin*, *135*, 943–973. https://doi.org/10.1037/a0017327

Schwartz, L. M. L., Woloshin, S. S., Black, W. C. W., & Welch, H. G. H. (1997). The role of numeracy in understanding the benefit of screening mammography. *Annals of Internal Medicine*, *127*, 966–972.

Smerecnik, C. M. R., Mesters, I., Kessels, L. T. E., Ruiter, R. A. C., de Vries, N. K., & de Vries, H. (2010). Understanding the positive effects of graphical risk information on comprehension: Measuring attention directed to written, tabular, and graphical risk information. *Risk Analysis*, *30*(9), 1387–1398. https://doi.org/10.1111/j.1539-6924.2010.01435.x

Spiegelhalter, D. (2017). Risk and uncertainty communication. *Annual Review of Statistics and its Application*, *4*, 31–60. https://doi.org/10.1146/annurev-statistics-010814-020148

Stacey, D., Légaré, F., Lewis, K., Barry, M. J., Bennett, C. L., Eden, K. B., Holmes-Rovner, M., Llewellyn-Thomas, H., Lyddiatt, A. Thomson, R., & Trevena, L. (2017). Decision aids for people facing health treatment or screening decisions. *The Cochrane Database of Systematic Reviews*, *4*, CD001431. https://doi.org/10.1002/14651858.CD001431.pub5

Tiede, K. E., Ripke, F., Degen, N., & Gaissmaier, W. (2020). When does the incremental risk format aid informed medical decisions? The role of learning, feedback, and number of treatment options. *Medical Decision Making*, *40*, 212–221. https://doi.org/10.1177/0272989X20904357

Trevena, L. J., Bonner, C., Okan, Y., Peters, E., Gaissmaier, W., Han, P. K. J., Ozanne, E., Timmermans, D., & Zikmund-Fisher, B. J. (2021). Current challenges when using numbers in patient decision aids: Advanced concepts. *Medical Decision Making*, *41*(7), 834–847. https://doi.org/10.1177/0272989X21996342

Zikmund-Fisher, B. J., Fagerlin, A., & Ubel, P. A. (2010). A demonstration of "less can be more" in risk graphics. *Medical Decision Making*, *30*(6), 661–670. https://doi.org/10.1177/0272989X10364244

S1 Supplemental Materials to Chapter 2

S1.1 Pilot Study

We conducted a pilot study prior to the main study to examine choice behavior and information search in the mixed condition in an exploratory manner. For the pilot study, we were primarily interested in which degree people would maximize EV and how many samples people would draw in the mixed condition. In this study, there were fewer choice problems and the set of choice problems consisted of a rather diverse selection of choice problems. For consistency, we conducted all analyses of the main study using the data of the pilot study. However, the choice problems were not primarily selected to estimate CPT parameters and less choices were made by participants. For these reasons, the parameter estimation was less reliable and the power to detect effects on CPT parameters was smaller compared to the main study.

S1.1.1 Method

A total of 246 participants (116 females; 130 males; 20–72 years; M_{age} = 36.6 years; SD_{age} = 11.5 years; 45.1% bachelor's degree or more) recruited via Amazon Mechanical Turk each made 50 choices between two monetary gambles in one of three conditions. The set of choice problems consisted of choice problems from the gain domain taken from a variety of sources (for choice problems, see Section S1.4). There were 38 target problems, eight problems with choices between the same option, and four attention-check problems. In the *description* and the *experience* conditions, participants made purely experience- and description-based choices. In the *mixed* condition, participants made choices between a described and an experienced option. We recruited twice as many participants from the mixed condition (n = 122) than from the description (n = 57) and experience (n = 67) condition. Following the choice task, participants filled out the same 7-item objective numeracy questionnaire as in the main study, but in English. Participants received the outcome of a randomly selected choice as a performance-contingent bonus (1 point = \$0.01; M = \$0.48, SD = \$0.24) in addition to their baseline compensation of \$3.00.

S1.1.2 Results

If not stated otherwise, computational modeling and analyses were conducted in the same way as in the main study (for details, see main article and section S3 of the Supplemental Materials).

S1.1.2.1 Subjective Representation of Outcomes and Probabilities

First, we examined whether we could replicate the differences between description- and experienced-based choices with regard to CPT parameters. We modeled choices using the same models as in the main study and compared the CPT parameters between the description and experience condition. Results can be found in Table S1.1. We could find a credible difference for outcome sensitivity α and probability sensitivity γ in line with the main study: In the experience (vs. description) condition, outcome sensitivity α was higher and probability sensitivity γ was lower. There was no credible difference in choice sensitivity φ between the two conditions. Note that because we only used gain-domain choice problems, we did not estimate loss aversion λ.

Next, we tested whether there were differences in CPT parameters between the described and the experienced option in the mixed condition. For this purpose, we modeled choices of the mixed condition using the CPT model with separate α and γ parameters for both options. Results of this model can be found in Table S1.2. There were no credible differences between the two options in terms of outcome sensitivity α and probability sensitivity γ.

As a next step, we used the joint-representation CPT model in which parameter values are constrained to be the same for both options and compared the parameter values of the mixed condition to those of the description and experience condition. For all three parameters, the group-level posterior means of the mixed condition fell descriptively between those of the description and the experience condition (see Table S1.1). In addition, in the mixed condition outcome sensitivity α was credibly different from the experience condition and probability sensitivity γ was credibly different from the description condition.

Finally, we tested whether there exists a preference for a certain learning format in the mixed condition beyond the subjective valuations. For this analysis, we ran the CPT model with same parameters but with a bias parameter β. The bias parameter β was not credibly different from 0, indicating that there is no bias towards a specific learning mode (group-level posterior mean = −0.04[−0.15–0.07]).

Although this study was not designed to estimate CPT parameters and therefore had less power to detect differences, the findings on CPT parameters overall replicated the pattern of results of the main study. First, we found differences in outcome sensitivity and probability sensitivity between description- and experience-based choices. Second, there were no differences in CPT parameters between learning modes within a choice.

Table S1.1: Posterior group-level mean parameters of the classical CPT model in the pilot study (95% HDI in squared brackets).

Parameter	Description condition (*n* = 73)	Experience condition (*n* = 78)	Mixed condition (*n* = 67)	Difference Descr. – Exp.	Difference Mixed – Descr.	Difference Mixed – Exp.
Outcome sensitivity α	0.70 [0.61–0.78]	0.96 [0.85–1.07]	0.76 [0.71–0.82]	**−0.26 [−0.40–−0.13]**	0.07 [−0.03–0.16]	**−0.19 [−0.32–−0.07]**
Probability sensitivity γ	1.14 [0.84–1.46]	0.70 [0.63–0.78]	0.78 [0.73–0.84]	**0.44 [0.12–0.76]**	**−0.36 [−0.68–−0.05]**	0.08 [−0.02–0.18]
Choice sensitivity φ	0.63 [0.37–0.92]	0.37 [0.21–0.56]	0.49 [0.36–0.62]	0.26 [−0.07–0.60]	−0.14 [−0.45–0.16]	0.12 [−0.11–0.34]

Note. Descr. = Description condition, Exp. = Experience condition, Mixed = Mixed condition. Credible differences are printed in boldface.

Table S1.2: Posterior group-level mean parameters of the CPT model with separate parameters for each option in the mixed condition in the pilot study (95% HDI in squared brackets).

Parameter	Described option	Experienced option	Difference described – experienced
Outcome sensitivity α	0.80 [0.73–0.85]	0.80 [0.74–0.87]	0.00 [0.00–0.00]
Probability sensitivity γ	0.84 [0.75–0.95]	0.80 [0.74–0.86]	0.05 [−0.06–0.17]
Choice sensitivity φ	0.44 [0.30–0.59]		

Third, the parameters of the mixed condition lied descriptively between those of the description and experience condition, although not all differences between the mixed and the description or experience condition were credible. However, the results show that the pattern of subjective representations in the mixed condition differs from the patterns in purely description- or experience-based choices.

S1.1.2.2 Search Behavior

We further examined whether people drew more samples per option in the mixed condition than in the experience condition and which factors of an experienced option and its alternative influence search effort. As expected, people drew larger samples per option in the mixed condition (M = 17.4, SD = 10.5) than in the experience condition (M = 10.7, SD = 7.6; $t(173.26) = 5.06$, $p < .001$).

Results on the determinants of sample size in the mixed and experience condition can be found in Table S1.3 and S1.4, respectively. In the mixed condition, all examined features of the described option (i.e., EV, number of outcomes, SD, and CV)

Table S1.3: Effect of the features of the choice problem on sample size in the experienced option of the mixed condition.

Predictor	*b*	*SE*	*p*
Intercept	14.93	1.12	< .001
DO: EV	**−0.06**	**0.02**	**< .001**
EO: EV	**0.05**	**0.02**	**< .001**
DO: Number of outcomes	**3.16**	**0.54**	**< .001**
EO: Number of outcomes	−0.45	0.53	.394
DO: SD	**0.06**	**0.03**	**.016**
EO: SD	0.01	0.03	.617
DO: CV	**−1.18**	**0.37**	**.002**
EO: CV	**2.19**	**0.37**	**< .001**
Absolute EV difference	**−0.12**	**0.02**	**< .001**
Absolute SD difference	**−0.08**	**0.03**	**.008**
Absolute CV difference	**2.25**	**0.46**	**< .001**

Note. DO = described option, EO = experienced option, EV = expected value, SD = standard deviation, CV = coefficient of variation. Significant predictors (p < .05) are printed in boldface.

Table S1.4: Effect of the features of the choice problem on sample size in the experience condition.

Predictor	*b*	*SE*	*p*
Intercept	10.04	0.92	< .001
AO: EV	0.00	0.01	.614
TO: EV	0.01	0.01	.263
AO: Number of outcomes	**1.65**	**0.31**	**< .001**
TO: Number of outcomes	**−0.87**	**0.31**	**.005**
AO: SD	-0.01	0.02	.612
TO: SD	0.03	0.02	.100
AO: CV	0.09	0.25	.723
TO: CV	0.22	0.25	.394
Absolute EV difference	**−0.05**	**0.01**	**< .001**
Absolute SD difference	**−0.04**	**0.02**	**.017**
Absolute CV difference	**1.99**	**0.28**	**< .001**

Note. AO = alternative option, TO = target option, EV = expected value, SD = standard deviation, CV = coefficient of variation. Significant predictors ($p < .05$) are printed in boldface.

were related to sample size, while for the experienced option, only EV and CV were related to sample size. Further, people sampled more outcomes from the experienced option when options were more similar in terms of EV and SD, but the opposite was true for CV. In the experience condition, the only feature which was related to sample size was the number of outcomes of the respective and the alternative option. However, absolute differences between the options in EV, SD, and CV were all significantly related to sample size. As the pilot study used gain-domain problems only, we could not test the effect of domain on sample size.

In sum, these results replicate the findings of the main study to some degree, although not completely. Most importantly, participants sample more outcomes per option in the mixed (vs. experience) condition which is line with the main study. For the effect of the options' features on sample size we could replicate the results of the main study for a multitude of features but not for all. However, when comparing the effects of the options' features between studies, it has to be considered that the choice problems of the pilot study were different from those in the main study (e.g., there were only gain-domain problems in the pilot study).

S1.1.2.3 EV Maximization

We also investigated choice behavior in terms EV maximization. The results showed that purely experience-based choices were more in line with EV maximization (M = .79; SD = .12) than description-based choices (M = .59; SD = .10; $t(122) = 9.93$, $p < .001$). EV maximization of the mixed condition (M = .67; SD = .11) lied between that of purely description- and experience-based choices and significantly differed from both description ($b = -.09$, SE = .02, $p < .001$) and experience (b = .11, SE = .02, $p < .001$).

S1.1.2.4 Numeracy

We further tested whether people higher (vs. lower) in objective numeracy drew larger samples in the mixed and the experience conditions. Mean objective numeracy in the pilot study was 3.66 (SD = 1.52). Numeracy was significantly associated with sample size per option (b = 1.82, SE = 0.70, p = .010). While people drew more samples in the mixed condition than in the experience condition (b = 6.69, SE = 1.36, $p < .001$), condition did not moderate the association of numeracy and sample size (b = 0.83, SE = 0.90, p = .356).

Further, we examined whether the subjective representations of people higher (vs. lower) in objective numeracy are more consistent between the described and the experienced option in the mixed condition. Outcome sensitivity α of the experienced option was negatively associated with the outcome sensitivity of the described option ($b = -0.92$, SE = 0.01, $p < .001$), but not with numeracy (b = 0.00, SE = 0.00, p = .988). The association of outcome sensitivity in the described and the experienced option was not moderated by objective numeracy ($b = -0.01$, SE = 0.01, p = .156). Probability sensitivity γ of the experienced option was positively associated with the probability sensitivity γ of the described option (b = 0.19, SE = 0.05, $p < .001$), but not with objective numeracy (b = 0.00, SE = 0.01, p = .478). Objective numeracy did not moderate the association of probability sensitivity in the described and experienced option ($b = -0.03$, SE = 0.04, p = .397).

Finally, we tested whether the preference for a particular learning mode is affected by objective numeracy. However, objective numeracy was not related to the bias parameter β (b = 0.02, SE = 0.02, p = .393).

S1.2 Choice Problems used in the Main Study

Table S1.5: Choice problems used in the main study.

	Option A				Option B			
ID	p1	o1	p2	o2	p1	o1	p2	o2
1	.34	24	.66	59	.42	47	.58	64
2	.88	79	.12	82	.20	57	.80	94
3	.74	62	.26	0	.44	23	.56	31
4	.05	56	.95	72	.95	68	.05	95
5	.25	84	.75	43	.43	7	.57	97
6	.28	7	.72	74	.71	55	.29	63
7	.09	56	.91	19	.76	13	.24	90
8	.63	41	.37	18	.98	56	.02	8
9	.88	72	.12	29	.39	67	.61	63
10	.61	37	.39	50	.60	6	.40	45
11	.08	54	.92	31	.15	44	.85	29
12	.92	63	.08	5	.63	43	.37	53
13	.78	32	.22	99	.32	39	.68	56
14	.16	66	.84	23	.79	15	.21	29
15	.12	52	.88	73	.98	92	.02	19
16	.29	88	.71	78	.29	53	.71	91
17	.31	39	.69	51	.84	16	.16	91
18	.17	70	.83	65	.35	100	.65	50
19	.91	80	.09	19	.64	37	.36	65
20	.09	83	.91	67	.48	77	.52	6
21	.44	14	.56	72	.21	9	.79	31
22	.68	41	.32	65	.85	100	.15	2
23	.38	40	.62	55	.14	26	.86	96
24	.62	1	.38	83	.41	37	.59	24
25	.49	15	.51	50	.94	64	.06	14
26	.05	60	.95	76	.84	95	.16	17
27	.73	75	.27	34	.90	56	.10	82
28	.16	-15	.84	-67	.72	-56	.28	-83
29	.13	-19	.87	-56	.70	-32	.30	-37
30	.29	-67	.71	-28	.05	-46	.95	-44
31	.82	-40	.18	-90	.17	-46	.83	-64
32	.29	-25	.71	-86	.76	-38	.24	-99
33	.60	-46	.40	-21	.42	-99	.58	-37
34	.48	-15	.52	-91	.28	-48	.72	-74
35	.53	-93	.47	-26	.80	-52	.20	-93
36	.49	-1	.51	-54	.77	-33	.23	-30
37	.99	-24	.01	-13	.44	-15	.56	-62
38	.79	-67	.21	-37	.46	0	.54	-97
39	.56	-58	.44	-80	.86	-58	.14	-97
40	.63	-96	.37	-38	.17	-12	.83	-69
41	.59	-55	.41	-77	.47	-30	.53	-61
42	.13	-29	.87	-76	.55	-100	.45	-28

43	.84	-57	.16	-90	.25	-63	.75	-30
44	.86	-29	.14	-30	.26	-17	.74	-43
45	.66	-8	.34	-95	.93	-42	.07	-30
46	.39	-35	.61	-72	.76	-57	.24	-28
47	.51	-26	.49	-76	.77	-48	.23	-34
48	.73	-73	.27	-54	.17	-42	.83	-70
49	.49	-66	.51	-92	.78	-97	.22	-34
50	.56	-9	.44	-56	.64	-15	.36	-80
51	.96	-61	.04	-56	.34	-7	.66	-63
52	.25	-94	.75	-37	.83	-49	.17	-11
53	.93	-55	.07	-17	.27	-88	.73	-35
54	.56	-4	.44	-80	.04	-46	.96	-58
55	.43	-91	.57	63	.27	-83	.73	24
56	.06	-82	.94	54	.91	38	.09	-73
57	.79	-70	.21	98	.65	-85	.35	93
58	.37	-8	.63	52	.87	23	.13	-39
59	.61	96	.39	-67	.50	71	.50	-26
60	.43	-47	.57	63	.02	-69	.98	14
61	.39	-70	.61	19	.30	8	.70	-37
62	.59	-100	.41	81	.47	-73	.53	15
63	.92	-73	.08	96	.11	16	.89	-48
64	.89	-31	.11	27	.36	26	.64	-48
65	.86	-39	.14	83	.80	8	.20	-88
66	.74	77	.26	-23	.67	75	.33	-7
67	.91	-33	.09	28	.27	9	.73	-67
68	.93	75	.07	-90	.87	96	.13	-89
69	.99	67	.01	-3	.68	74	.32	-2
70	.48	58	.52	-5	.40	-40	.60	96
71	.07	-55	.93	95	.48	-13	.52	99
72	.97	-51	.03	30	.68	-89	.32	46
73	.86	-26	.14	82	.60	-39	.40	31
74	.88	-90	.12	88	.80	-86	.20	14
75	.87	-78	.13	45	.88	-69	.12	83
76	.96	17	.04	-48	.49	-60	.51	84
77	.38	-49	.62	2	.22	19	.78	-18
78	.28	-59	.72	96	.04	-4	.96	63
79	.50	98	.5	-24	.14	-76	.86	46
80	.18	-19	.82	73	.94	58	.06	-54
81	.39	76	.61	-7	.06	-65	.94	37
82	.50	-20	.50	60	1	0		
83	.50	-30	.50	60	1	0		
84	.50	-40	.50	60	1	0		
85	.50	-50	.50	60	1	0		
86	.50	-60	.50	60	1	0		
87	.50	-70	.50	60	1	0		
88	.10	40	.90	32	.10	77	.90	2
89	.20	40	.80	32	.20	77	.80	2
90	.30	40	.70	32	.30	77	.70	2
91	.40	40	.60	32	.40	77	.60	2

92	.50	40	.50	32	.50	77	.50	2
93	.60	40	.40	32	.60	77	.40	2
94	.70	40	.30	32	.70	77	.30	2
95	.80	40	.20	32	.80	77	.20	2
96	.90	40	.10	32	.90	77	.10	2
97	1	40			1	77		
98	.80	4	.20	0	1	3		
99	.20	4	.80	0	.25	3	.75	0
100	1	-3			.10	-32	.90	0
101	1	-3			.80	-4	.20	0
102	.10	32	.90	0	1	3		
103	.03	32	.97	0	.25	3	.75	0
104	.10	20	.90	0	.10	20	.90	0
105	.20	20	.80	0	.20	20	.80	0
106	.50	20	.50	0	.50	20	.50	0
107	.80	20	.20	0	.80	20	.20	0
108	.90	20	.10	0	.90	20	.10	0
109	.80	91	.20	63	.60	15	.40	22
110	.45	57	.55	63	.70	23	.30	12
111	.61	-24	.39	-19	.48	-78	.52	-59
112	.60	-3	.40	-22	.37	-50	.63	-60

Note. Choice problems taken from Rieskamp (2008; IDs 1–81); Gächter et al. (2007; IDs 82–87); Holt & Laury (2002; IDs 88–97); Hertwig et al. (2004; IDs 98–103); and Ert & Trautmann (2014; IDs 104–108). Attention-check problems (IDs 109–112) were developed by us.

S1.3 Additional Analyses for Main Study

In the following, we present further analyses on search effort in the experience condition, expected value (EV) maximization across conditions, and the role of numeric abilities in choice and information search in the mixed condition.

S1.3.1 Search Effort in the Experience Condition

We studied which features of an experienced option and its experienced alternative affect search effort of that experienced option. For that purpose, we examined search effort in the experience condition for each option individually and disentangled the influence of the features of an experienced option and its experienced alternative on search effort. In particular, we conducted the same analysis as for the mixed condition, except that the dependent variable was the sample size of one of the two experienced options (i.e., the target option) and each option was treated once as the target option and once as alternative option. Results of this analysis can be found in Table S1.6 and show that the choice context matters also in the experience condition. For the alternative option, the effects of the features were similar as in the mixed condition (where the described option was the alternative option): EV was negatively and SD was positively associated with sample size, whereas number of outcomes and CV did not influence sample size. However, different features of the target option affected search effort in the experience condition compared to the mixed condition. Sample size was associated with the number of outcomes and the SD of the target option. Finally, as in the mixed condition people sampled more outcomes the closer the EVs were in the experience condition, but sample size was not affected by differences in SD or CV. In contrast to the mixed condition, participants drew significantly fewer samples in the loss domain than in the gain domain ($b = -4.45$, $SE = 0.97$, $p < .001$).

Table S1.6: Effect of the features of the choice problem on sample size in the experience condition.

Predictor	*b*	*SE*	*p*
Intercept	17.43	0.98	< .001
AO: EV	**−0.02**	**0.00**	**< .001**
TO: EV	0.01	0.00	.118
AO: Number of outcomes	0.16	0.30	.599
TO: Number of outcomes	**−1.20**	**0.30**	**< .001**
AO: SD	**0.03**	**0.01**	**< .001**
TO: SD	**0.01**	**0.01**	**.035**
AO: CV	−0.03	0.07	.628
TO: CV	−0.03	0.07	.680
Absolute EV difference	**−0.04**	**0.01**	**< .001**
Absolute SD difference	−0.01	0.01	.081
Absolute CV difference	0.03	0.07	.709

Note. AO = alternative option, TO = target option, EV = expected value, SD = standard deviation, CV = coefficient of variation. Significant predictors ($p < .05$) are printed in boldface.

S1.3.2 EV Maximization

Besides subjective representations of outcomes and probabilities, another key dimension along which differences between description- and experience-based choices have been observed is people's tendency to choose the option with the higher expected value, a benchmark of normative decision making. In particular, EV maximization is higher in purely experienced-based choices than in purely description-based choices (Wulff et al., 2018). How well do people choose when they have to compare information from two different learning modes? As the integration of information could reflect a cognitive burden which consumes cognitive resources, choices in a situation with mixed learning modes could be less consistent with EV maximization than choices based on the same learning mode for all options. On the other hand, the finding that experience-based choices are more consistent with EV maximization is partially explained by amplified differences between EVs and thus easier choices caused by especially small sample sizes (Hertwig & Pleskac, 2010; Wulff et al., 2018). Following this argumentation, choices in a mixed condition could be easier than choices between description-based options, while being more difficult than choices between experienced-based options. Alternatively, EV maximization could be similar to either purely experience-based or description-based choices if people translate one representation into another as outlined in the main text.

To test these alternative hypotheses, we examined how often participants chose the option with the higher EV—thus deciding in line with EV maximization—in the different conditions. In the experience and the mixed conditions, the expected value of the experienced options was calculated as the mean of the sampled outcomes (cf. Wulff et al., 2018). In this analysis, we excluded trials in which EV were the same for both options (0.4% of trials). The results showed that when participants chose between two experienced options, they chose the option with the higher EV more often than when participants chose between two described options ($M_{\text{experience}} = .70$, $SD_{\text{experience}} = .08$ vs. $M_{\text{description}} = .64$, $SD_{\text{description}} = .07$; $t(149) = 4.86$, $p < .001$). Next, we compared EV maximization of the mixed condition ($M_{\text{mixed}} = .69$, $SD_{\text{mixed}} = .08$) with EV maximization of the description and experience conditions. For that purpose, we conducted a linear regression with two condition dummy variables as predictors (first variable coded as 0 = mixed, 1 = description, second variables coded as 0 = mixed, 1 = experience) and proportion of choices in line with EV maximization as dependent variable. Participants in the mixed condition chose the option with the higher EV significantly more often than in the description condition (*b* = −.05, *SE* = .01, *p* < .001), but not more or less often as in the experience condition (*b* = .00, *SE* = .01, *p* = .714).

These results replicate previously found difference between description- and experience-based choices and suggest that choices in the mixed condition are similarly good as in the experience condition. However, this finding is difficult to reconcile with the amplification effect (Hertwig & Pleskac, 2010). Moreover, as sample size per option was higher in the mixed condition than in the experience condition and thus choices became more difficult, the amplification effect would have predicted even worse choices in the mixed condition. Nevertheless, our findings suggest that information integration in the mixed condition does not incur particularly high cognitive costs, but even leads to relatively good choices in terms of EV maximization.

S1.3.3 The Role of Numeracy

In the following, we study the role of numeracy in choice and search behavior.

S1.3.3.1 Objective and Subjective Numeracy and Sample Size

People higher in objective numeracy, the ability to use probabilistic and mathematical concepts, have been shown to draw larger samples in purely experience-based choices than people lower in numeracy (Ashby, 2017; Lejarraga, 2010; Traczyk et al., 2018). First, we aimed to test whether this effect holds in the mixed condition with only one experienced option. Second, because all the studies on the effect of numeracy on sample size including our pilot study only measured the actual numeric abilities (i.e., objective numeracy; Ashby, 2017; Lejarraga, 2010; Traczyk et al., 2018), it is unclear whether these abilities are responsible for that effect or rather the preference for numbers drive it. This subjective numeracy correlates with objective numeracy but explains unique variance beyond it (Nelson et al., 2013; Peters & Bjalkebring, 2015; Peters et al., 2019). Because participants can choose how much information they want to gather, it is possible that sample size rather depends on the perceived numerical abilities and the preference for numbers (i.e., subjective numeracy) rather than the objective numeracy. To examine this possibility, participants were asked to fill out the German translation of the subjective numeracy scale (Fagerlin et al., 2007) before starting the choice task. This 7-item measure asked participants to rate their numerical abilities and their preference for numbers on a 6-point scale (Cronbach's α = .76; one item of the original 8-item scale was not used because it was specific to the US; see Galesic & Garcia-Retamero, 2010). Objective numeracy was assessed after the choice task using the German translation of a

7-item questionnaire which combined the measures by Schwartz et al. (1997) and a variation of the Berlin Numeracy Test (Cokely et al., 2012).

To test the effect of objective and subjective numeracy on sample size per option, we conducted a linear regression with objective numeracy, subjective numeracy (both mean-centered), condition (dummy-coded as 0 = experience condition, 1 = mixed condition), and their interactions as predictors. Dependent variable was sample size per option (in the experience condition, this was the mean sample size across both options).

Mean objective numeracy was 4.38 (SD = 1.49) and mean subjective numeracy was 4.12 (SD = 0.82). The results showed that people sampled more outcomes per option in the mixed condition than in the experience condition (b = 7.31, SE = 1.77, p < .001). However, neither objective numeracy (b = 0.47, SE = 0.79, p = .549) nor subjective numeracy (b = 0.72, SE = 1.45, p = .622) was significantly associated with sample size. There were no significant interactions.

Our study could not replicate the finding that people higher (vs. lower) in objective numeracy draw more samples in the mixed or experience condition (Ashby, 2017; Lejarraga, 2010; Traczyk et al., 2018). Possibly, our participant sample (mainly undergraduate students) was too homogeneous with regard to education level and thus numeracy to find reliable effects of objective or subjective numeracy.

S1.3.3.2 Numeracy and Consistency Across Learning Modes

We also investigated the role of numeric abilities in the subjective representation of outcomes and probabilities. People higher (vs. lower) in objective numeracy choose more consistently between purely description- and experienced-based choices (Ashby, 2017). Therefore, we tested whether the subjective representation of outcomes and probabilities in the mixed condition is more consistent between the described and experienced option for people who score higher (vs. lower) in objective numeracy. To analyze how objective numeracy moderates the relationship between subjective representations in the described and the experienced option, we conducted two linear regressions. In the first regression, the individual-level posterior mean for outcome sensitivity α in the experienced option was the dependent variable and the individual-level posterior mean for outcome sensitivity α in the described option, objective numeracy (mean-centered), and their interactions were predictors. In the second regression, we used probability sensitivity γ instead of outcome sensitivity α.

Outcome sensitivity α of the experienced option was negatively associated with outcome sensitivity α of the described option (b = −0.93, SE = 0.04, p < .001), but not with numeracy (b = 0.00, SE = 0.00, p = .647). The association of outcome sensitivity of the described and the experienced option was not moderated by objective numeracy (b = 0.02, SE = 0.03, p = .402). Probability sensitivity γ of the experienced option was positively associated with probability sensitivity γ of the described option (b = 0.17, SE = 0.07, p = .017), but again not with objective numeracy (b = 0.00, SE = 0.01, p = .910). The association of probability sensitivity of the described and the experienced option was not moderated by objective numeracy (b = 0.09, SE = 0.05, p = .077).

The results show that people higher (vs. lower) in objective numeracy did not have a more consistent subjective representation of probabilities across options in the mixed condition. However, due to the hierarchical Bayesian modeling approach the variance in the individual-level estimates is reduced compared to when estimating parameters individually. Therefore, it is unclear whether this issue made it harder to find a significant effect, so that more research is needed to investigate the role of objective numeracy in choice consistency across learning modes.

S1.3.3.3 Numeracy and Preference for Learning Modes

When people could choose between making description- and experience-based choices, numeracy did not affect the preference for a choice condition (Lejarraga, 2010). However, we studied whether preference for a learning mode in choices between a described and experienced option is affected by objective numeracy. To test this, we ran the CPT model of the mixed condition which restricted parameters to be the same across options and which included the bias parameter β. As a reminder, $\beta > 0$ reflects a preference for the description, whereas $\beta < 0$ reflects a preference for experience. We conducted a regression with β as dependent variable and objective numeracy (mean-centered) as predictor. People higher (vs. lower) in objective numeracy did not have a stronger preference for the described option (b = 0.03, SE = 0.01, p = .064).

S1.4 Choice Problems used in the Pilot Study

Table S1.7: Choice problems used in the pilot study.

	Option A				Option B			
ID	p1	o1	p2	o2	p1	o1	p2	o2
1	.80	40	.20	0	1	30		
2	.20	40	.80	0	.25	30	.75	0
3	.10	32	.90	0	1	3		
4	.03	32	.97	0	.25	3	.75	0
5	.90	50	.10	0	1	45		
6	.11	55	.89	0	1	5		
7	.07	42	.93	6	1	8		
8	.92	90	.08	36	1	86		
9	1	53			1	53		
10	1	22			1	22		
11	.50	40	.50	0	.50	40	.50	0
12	.30	78	.70	43	.30	78	.70	43
13	.90	40	.10	0	.90	40	.10	0
14	.05	80	.95	8	.05	80	.95	8
15	.08	12	.92	69	.08	12	.92	69
16	.90	0	.10	40	.90	0	.10	40
17	.91	21	.09	54	.61	10	.39	72
18	.90	44	.10	8	.35	6	.65	84
19	.91	27	.09	64	.45	40	.55	25
20	.09	7	.91	52	.40	74	.60	30
21	.68	41	.32	65	.85	96	.15	2
22	.93	37	.07	2	.54	27	.46	22
23	.92	35	.08	97	.35	22	.65	53
24	.80	54	.20	21	.49	98	.51	3
25	.05	56	.95	72	.95	68	.05	95
26	.05	60	.95	76	.84	95	.16	17
27	.12	52	.88	73	.98	92	.02	19
28	.98	76	.02	37	.82	49	.18	50
29	.19	30	.81	97	.14	85	.86	82
30	.88	79	.12	82	.20	57	.80	94
31	.08	54	.92	31	.15	44	.85	29
32	.10	45	.90	14	.14	25	.86	27
33	.05	95	.95	68	1	71		
34	.05	95	.95	68	.05	90	.95	70
35	.05	56	.95	72	1	71		
36	.09	7	.91	52	.09	95	.91	43
37	.09	7	.91	52	.09	1	.91	53
38	.09	95	.91	43	.40	74	.60	30
39	.50	59	.50	12	.30	41	.70	47
40	.42	20	.58	80	.45	30	.55	60
41	.33	99	.67	56	.60	70	.40	60
42	.77	23	.23	11	.51	14	.49	28

43	.50	44	.50	77	1	55		
44	.27	68	.73	35	1	51		
45	.40	92	.60	10	1	34		
46	.39	23	.61	26	1	25		
47	.50	61	.50	78	1	34		
48	.33	32	.67	22	1	68		
49	.25	95	.75	57	.40	31	.60	21
50	.45	31	.55	9	.30	56	.70	87

Note. Choice problems taken and adapted from Hertwig et al. (2004; IDs 1–4); Camilleri & Newell (2011; IDs 5–6); Glöckner et al., 2016 (IDs 7–8); Ert & Trautmann (2014; IDs 11, 13, and 16); Glöckner et al. (2012; IDs 17–20 and 22–23); Rieskamp, 2008 (2008; IDs 21 and 24–32). All other choice problems (IDs 9–10, 12, 14–15, and 33–50) were developed by us.

References

Ashby, N. J. S. (2017). Numeracy predicts preference consistency: Deliberative search heuristics increase choice consistency for choices from description and experience. *Judgment and Decision Making*, *12*, 128–139.

Camilleri, A. R., & Newell, B. R. (2011). Description- and experience-based choice: Does equivalent information equal equivalent choice? *Acta Psychologica*, *136*, 276–284. https://doi.org/10.1016/j.actpsy.2010.11.007

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., & Garcia-Retamero, R. (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making*, *7*, 25–47.

Ert, E., & Trautmann, S. T. (2014). Sampling experience reverses preferences for ambiguity. *Journal of Risk and Uncertainty*, *49*, 31–42. https://doi.org/10.1007/s11166-014-9197-9

Fagerlin, A., Zikmund-Fisher, B. J., Ubel, P. A., Jankovic, A., Derry, H. A., & Smith, D. M. (2007). Measuring numeracy without a math test: Development of the Subjective Numeracy Scale. *Medical Decision Making*, *27*, 672–680. https://doi.org/10.1177/0272989X07304449

Gächter, S., Johnson, E. J., & Herrmann, A. (2007). Individual-level loss aversion in riskless and risky choices (IZA Discussion Paper No. 2961). https://ftp.iza.org/dp2961.pdf.

Galesic, M., & Garcia-Retamero, R. (2010). Statistical numeracy for health: A cross-cultural comparison with probabilistic national samples. *Archives of Internal Medicine*, *170*, 462–468. https://doi.org/10.1001/archinternmed.2009.481

Glöckner, A., Hilbig, B. E., Henninger, F., & Fiedler, S. (2016). The reversed description-experience gap: Disentangling sources of presentation format effects in risky choice. *Journal of Experimental Psychology: General*, *145*, 486–508. https://doi.org/10.1037/a0040103

Glöckner, A., Fiedler, S., Hochman, G., Ayal, S., & Hilbig, B. E. (2012). Processing differences between descriptions and experience: a comparative analysis using eye-tracking and physiological measures. *Frontiers in Psychology*, *3*, Article 173. https://doi.org/10.3389/fpsyg.2012.00173

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*, 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x

Hertwig, R., & Pleskac, T. J. (2010). Decisions from experience: Why small samples? *Cognition*, *115*, 225–237. https://doi.org/10.1016/j.cognition.2009.12.009

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*, 1644–1655. https://doi.org/10.1257/000282802762024700

Lejarraga, T. (2010). When experience is better than description: Time delays and complexity. *Journal of Behavioral Decision Making*, *23*, 100–116. https://doi.org/10.1002/bdm.666

Nelson, W. L., Moser, R. P., & Han, P. K. J. (2013). Exploring objective and subjective numeracy at a population level: Findings from the 2007 Health Information National Trends Survey (HINTS). *Journal of Health Communication*, *18*, 192–205. https://doi.org/10.1080/10810730.2012.688450

Pachur, T., Schulte-Mecklenbeck, M., Murphy, R. O., & Hertwig, R. (2018). Prospect theory reflects selective allocation of attention. *Journal of Experimental Psychology: General*, *147*, 147–169. https://doi.org/10.1037/xge0000406

Peters, E., & Bjalkebring, P. (2015). Multiple numeric competencies: When a number is not just a number. *Journal of Personality and Social Psychology*, *108*, 802–822. https://doi.org/10.1037/pspp0000019

Peters, E., Tompkins, M. K., Knoll, M. A. Z., Ardoin, S. P., Shoots-Reinhard, B., & Meara, A. S. (2019). Despite high objective numeracy, lower numeric confidence relates to worse financial and medical outcomes. *Proceedings of the National Academy of Sciences of the United States of America*, *116*, 19386–19391. https://doi.org/10.1073/pnas.1903126116

Rieskamp, J. (2008). The probabilistic nature of preferential choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*, 1446–1465. https://doi.org/10.1037/a0013646

Schwartz, L. M., Woloshin, S., Black, W. C., & Welch, H. G. (1997). The role of numeracy in understanding the benefit of screening mammography. *Annals of Internal Medicine, 127*, 966–972. https://doi.org/10.7326/0003-4819-127-11-199712010-00003

Traczyk, J., Lenda, D., Serek, J., Fulawka, K., Tomczak, P., Strizyk, K., Polec, A., Zjawiony, P., & Sobkow, A. (2018). Does fear increase search effort in more numerate people? An experimental study investigating information acquisition in a decision from experience task. *Frontiers in Psychology, 9*, Article 1203. https://doi.org/10.3389/fpsyg.2018.01203

Wulff, D. U., Mergenthaler-Canseco, M., & Hertwig, R. (2018). A meta-analytic review of two modes of learning and the description-experience gap. *Psychological Bulletin*, *144*, 140–176. https://doi.org/10.1037/bul0000115

S2 Supplemental Materials to Chapter 3

S2.1 Screenshot of Trial Screens

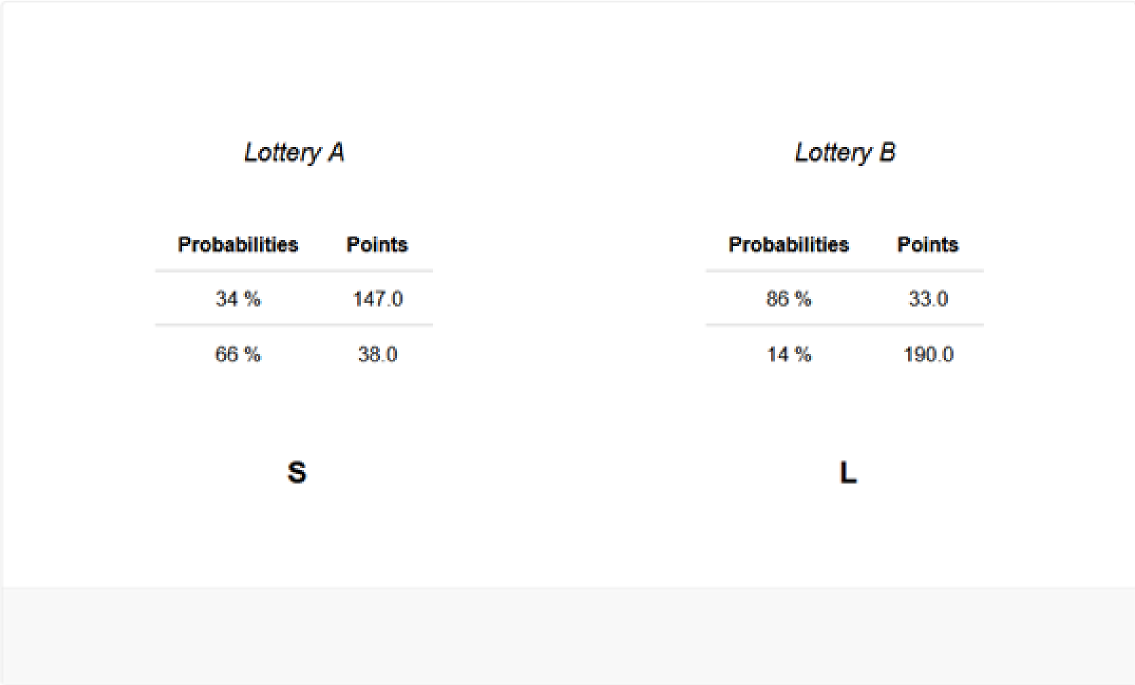

Figure S2.1: Screenshot of trial screen in Experiment 1.

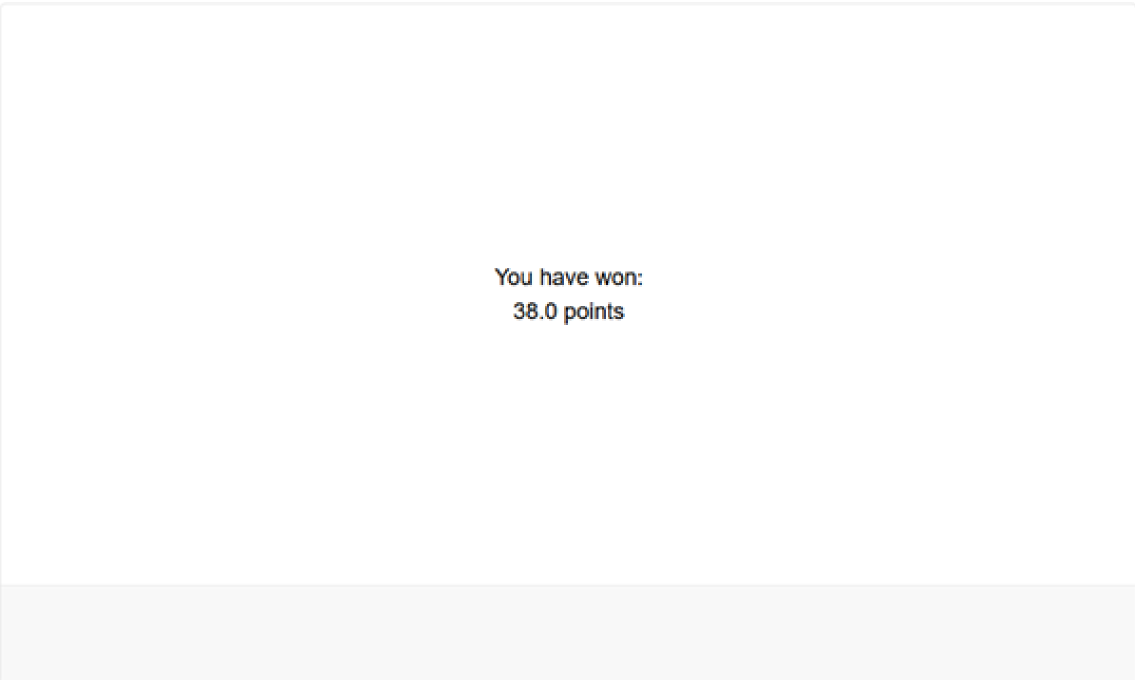

Figure S2.2: Screenshot of feedback (presented for 1000 ms).

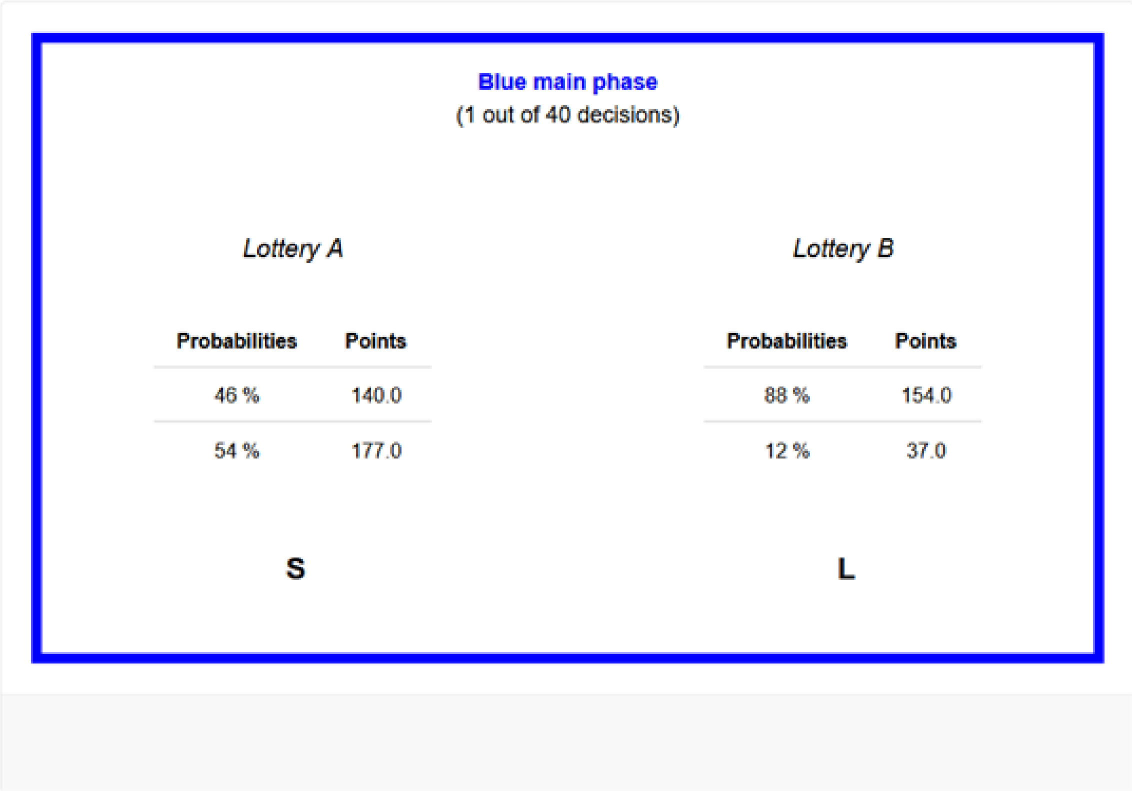

Figure S2.3: Screenshot of trial screen in Experiments 2 and 3.

S2.2 Behavioral Results: Accuracy

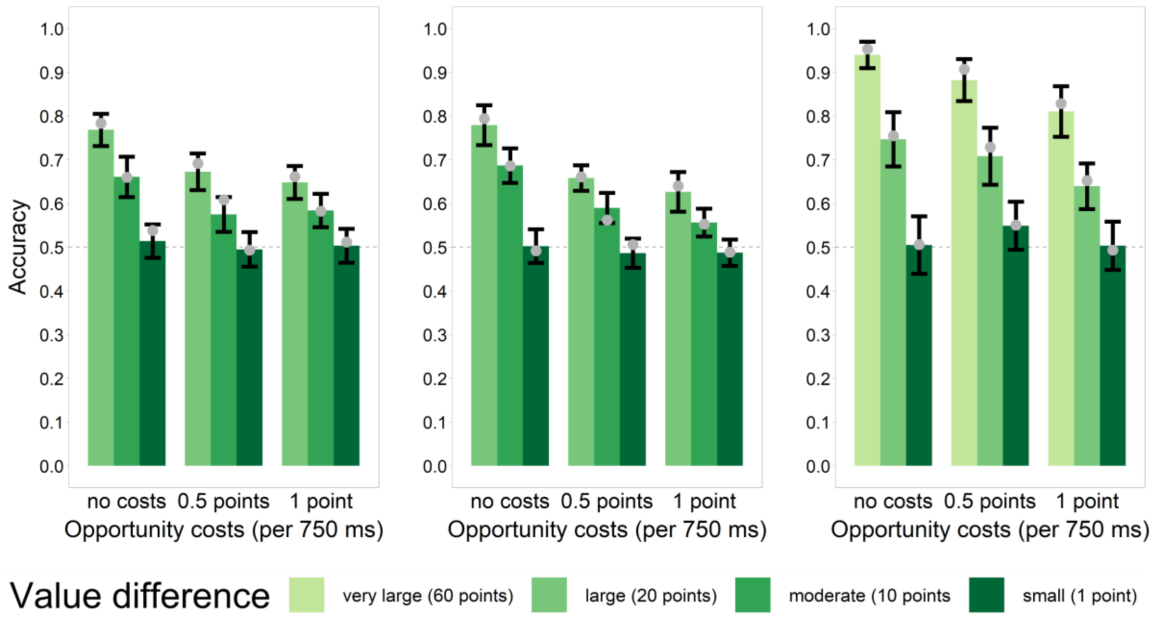

Figure S2.4: Accuracy in each condition (error bars represent 95% confidence intervals) for Experiment 1 (left panel), Experiment 2 (middle panel), and Experiment 3 (right panel). Grey points represent means of the posterior predictive checks generated by the estimated DDM parameters.

S2.3 Modeling Results: Drift Rate and Non-Decision Time

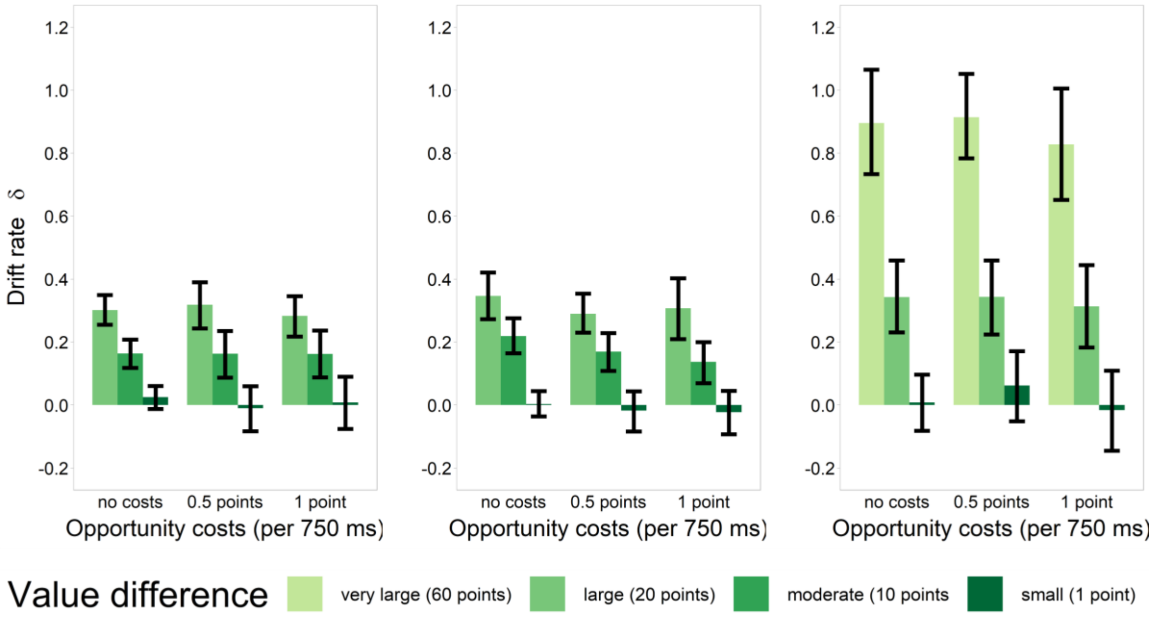

Figure S2.5: Estimated drift rate δ (group-level posterior means; error bars represent 95% HDIs) in each condition for Experiment 1 (left panel), Experiment 2 (middle panel), and Experiment 3 (right panel).

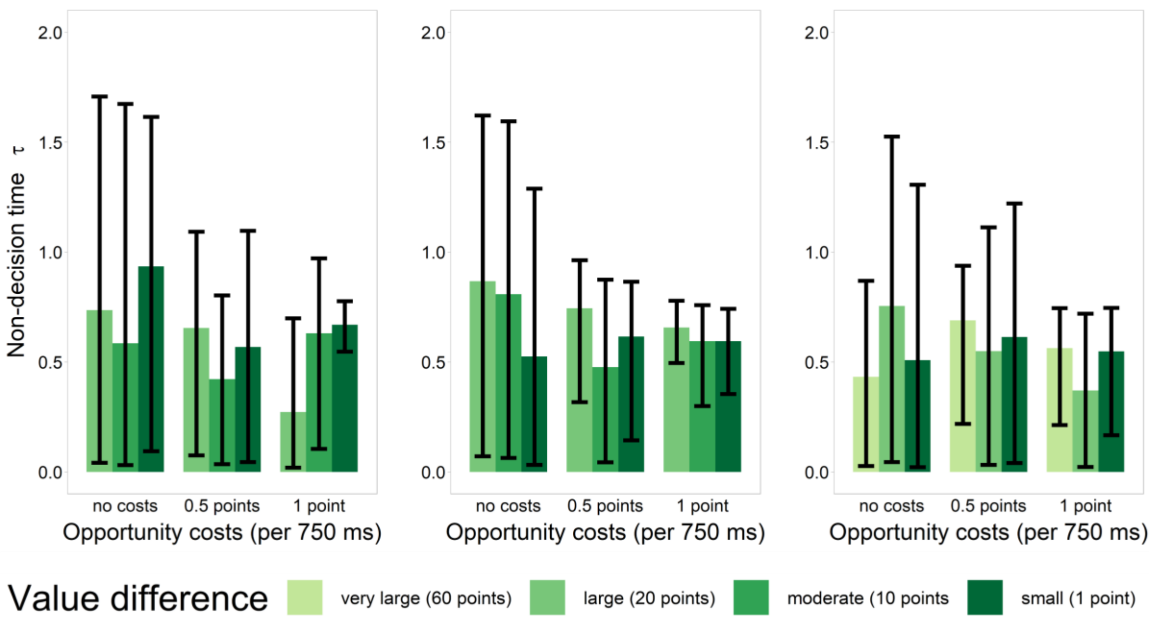

Figure S2.6: Estimated non-decision time τ (group-level posterior means; error bars represent 95% HDIs) in each condition for Experiment 1 (left panel), Experiment 2 (middle panel), and Experiment 3 (right panel).

S3 Supplemental Materials to Chapter 4

S3.1 Description of Pilot Study

Prior to the main study, we conducted a pilot study to determine appropriate time limits for the time-pressure conditions. We aimed to identify time limits which would urge participants to respond fast but still allowed them to answer the questions within the given time. For this purpose, we conducted a study which was similar to the main study but only included the numerical, graphical, and inconsistent conditions without time pressure. Also, we did not assess numeracy or graph literacy. Sixty participants (34 female, 24 male, 2 nonbinary, 18–71 years, M_{age} = 33.0, SD_{age} = 12.1, 65.0% with a college degree or more) recruited via Prolific Academic took part in the pilot study.

For the decision, the median response time was 34.42 seconds (M = 41.47, SD = 26.39). Participants were faster at answering the knowledge questions, but response times differed considerably between the types of knowledge questions. For gist knowledge questions, the median response time was 14.40 seconds (M = 19.21, SD = 19.75). For verbatim knowledge (reading-off items) questions, the median response time was 13.02 seconds (M = 15.33, SD = 7.62). For verbatim knowledge questions (computing-differences items), the median response time was 21.77 seconds (M = 24.81, SD = 11.81).

For the main study, we decided to choose time limits in which about half of the participants would be expected to answer the questions without a time limit (see Table 4.2 in the main text).

S3.2 Presentation Formats and Screenshots of Question Page

Medication A

Benefits	Side effects
63 out of 100	34 out of 100

Medication B

Benefits	Side effects
41 out of 100	21 out of 100

Medication C

Benefits	Side effects
46 out of 100	21 out of 100

Medication D

Benefits	Side effects
43 out of 100	25 out of 100

Medication E

Benefits	Side effects
67 out of 100	37 out of 100

Medication F

Benefits	Side effects
67 out of 100	31 out of 100

Figure S3.1: Presented medical information as presented in the numerical conditions.

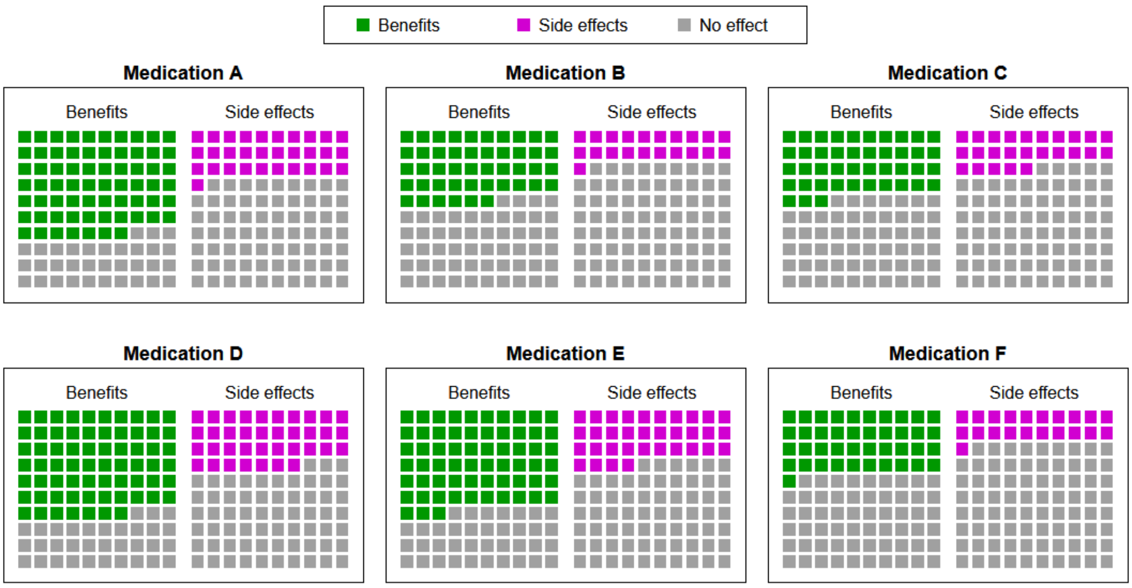

Figure S3.2: Presented medical information as presented in the graphical conditions.

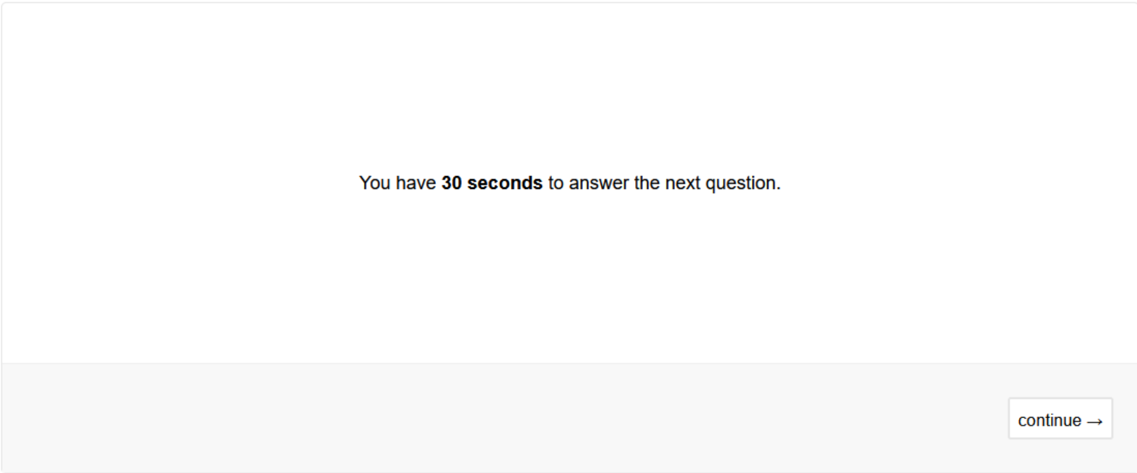

Figure S3.3: Screenshot of the announcement on how much time participants have to answer the following question.

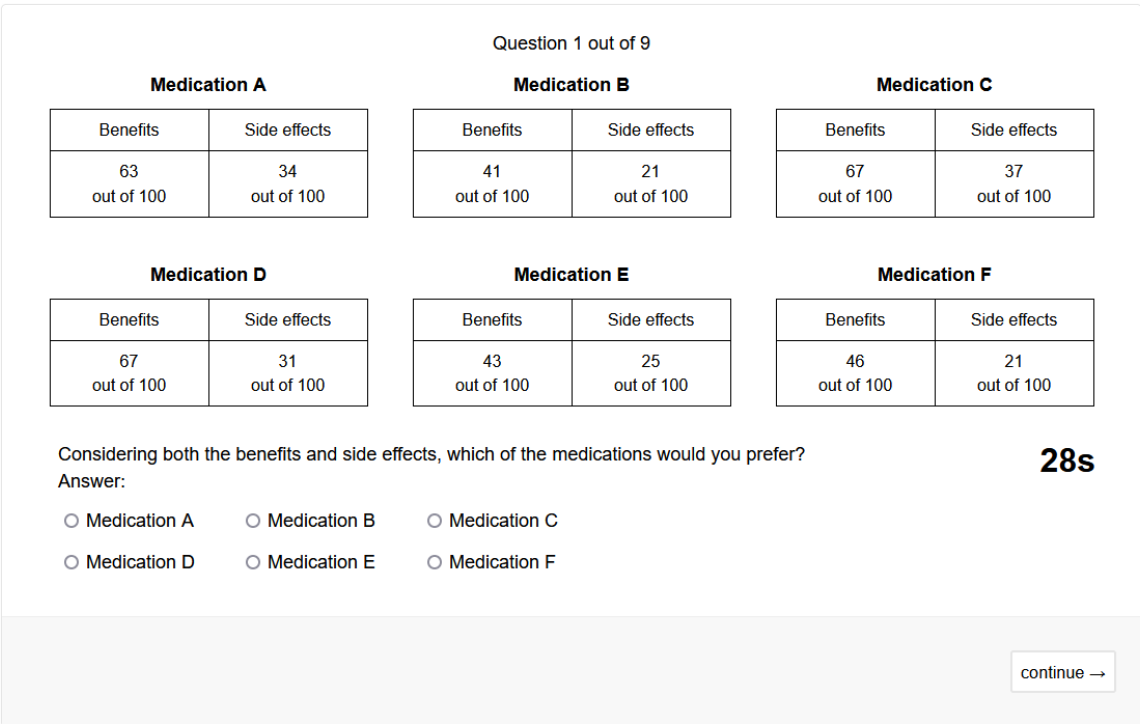

Figure S3.4: Screenshot of a question screen in a condition with time pressure. Note the display of the remaining time in the lower-left corner. When 5 or less seconds were left, the color of the time turned magenta.

Author Contributions

Chapter 1

Synopsis:	KET

Chapter 2

Tiede, K. E., Gaissmaier, W., & Pachur, T. (2021). Choosing between described and experienced risky options: No gap, but a similar evaluation of options.

Idea and study design:	KET, WG
Data collection:	KET
Data analysis:	KET, TP
Preparation of first manuscript:	KET
Critical revisions:	KET, TP, WG

Chapter 3

Tiede, K. E., Zilker, V., & Pachur, T. (2021). Good time, bad time: Do people invest processing effort adaptively in decision making with opportunity costs?

Idea and study design:	KET, VZ, TP
Data collection:	KET
Data analysis:	KET, VZ
Preparation of first manuscript:	KET
Critical revisions:	KET, VZ, TP

Chapter 4

Tiede, K. E., & Gaissmaier, W. (2021). Graphical representations of medical information require more cognitive effort than numbers, but are preferred.

Idea and study design:	KET, WG
Data collection:	KET
Data analysis:	KET
Preparation of first manuscript:	KET
Critical revisions:	KET, WG