MOTIVATION AND VOLITION IN ECONOMIC DECISIONS

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Abstract

People face economic decisions on a daily basis. Quite often, these decisions involve high stakes and some degree of personal risk, as choices produce real consequences that set the course for future actions. Although decades of decision research in the intersection of psychology, behavioral economics, and neuroscience have much advanced our knowledge about the psychological underpinnings of economic decisions, several academic disputes remain unsettled. Indeed, surprisingly little is known about the role of motivation and volition in guiding economic decisions. Certainly, people’s motives, goals, and their expectations of attractive rewards are important drivers of decision making. Yet, motivation and volition cannot be reduced to goals and incentives. The cognitive mechanisms underlying economic decisions are rather complex, and motivation and volition may impact decisions at the level of these cognitive processes.

This dissertation considers the role of motivation and volition in economic decisions by examining the impact of experimentally induced motivational and volitional states of mind on economic choices and decision processes. Using different methods and decision making paradigms, four experiments provide novel evidence that informs the ongoing debates in motivation research, decision science, and psychophysiology. In short, Experiments 1a and 1b explore the possibility of interactive effects between motivation, volition, and financial incentives in determining economic performance. Moving on to the level of decision processes, Experiment 2 examines the impact of motivation and volition on decision processes under risk. Decision times, eye movements, and pupil dilations provide process measures of cognitive effort, pre-decisional information search, and affective arousal, respectively. Finally, Experiment 3 investigates how particular decision attributes relate to affective and motivational processes in decisions under risk.

The findings of the present dissertation can be summarized in terms of four main conclusions. First, incentives are effective for improving economic performance when the payment of attractive monetary rewards is contingent on performance. Yet, higher
incentives do not further improve performance. Second, the experimental manipulation of motivational and volitional mindsets does not directly affect choices, but notably impacts decision processes. Third, the influence of motivation and volition on economic decisions appears to depend on the appropriate incentivization of the task at hand. Fourth, risky choice attributes that entail no gain at all, i.e., zero-outcomes, elicit high levels of affective arousal and motivational avoidance tendencies that guide selective attention and decision making in the lottery choice paradigm. The implications of these findings are discussed for theory development in motivation research and decision science, as well as in terms of their practical implications for decision making in managerial contexts and other high-stakes decision environments.
Zusammenfassung


x
INTRODUCTION

What drives human decision making? A rich tradition of research on judgment and decision making in psychology, and more recent insights from behavioral economics and neuroscience, have led to a much enhanced understanding of the psychological underpinnings of all sorts of human decisions. From deciding upon the big questions of life, which may well affect one’s long-term economic prosperity, to everyday consumer choices; from tough decisions in unfortunate moral dilemmas to the choice of when to get up in the morning; from complex predictions about our own personal future to choose here and now which of two simultaneously pressing, tedious tasks first to approach – undoubtedly, the picture of human decision making is incredibly diverse.

Some of these choices may seem trivial, like deciding between two brands of Italian pasta for tomorrow’s dinner. Other choices, though, may seriously affect people’s well-being and economic perspectives in the long run, for example, educational or investment decisions. Regardless of the personal relevance or emotional involvement, the cognitive mechanisms underlying human judgments and decisions are rather complex. Scholarly attention has grasped many important psychological aspects of judgment and decision making and thoroughly explored its antecedents and the involved cognitive processes. A host of formal choice models exist to explain decisions in various contexts. Yet, the complexity of the psychological dimensions of judgments and decisions is not yet fully understood. Despite decades of decision research, our knowledge about some of the most pressing questions is still surprisingly limited. To date, several academic disputes remain unsettled.

One understudied area concerns the role of motivation and volition in judgment and decision making generally, and in research about economic decisions in particular. The study of goals (e.g., Locke & Latham, 2002) and financial incentives (e.g., Camerer & Hogarth, 1999; Deci, Koestner, & Ryan, 1999) has answered many questions about
how motivation may influence decisions. But little is known about the cognitive mechanisms that drive motivational processes beyond goals and financial incentives. This is similarly true for the study of volition, i.e., the psychological mechanisms underlying willful self-control. Research on if-then action plans (Gollwitzer, 1999) and the limits of self-regulatory resources (Baumeister, 2002) have advanced our knowledge of how self-control may influence decisions (but see also Hagger & Chatzisarantis, 2016, reporting on a large scale multi-lab project which failed to replicate the resource depletion effect). Yet, a broader approach to integrate volitional processes more generally in theories of judgment and decision making is missing.

Another question regards the role of attention in guiding decisions. Visual attention is well known to play an active part in decision making (e.g., Orquin & Mueller Loose, 2013). Most formal choice models, however, do not explicitly incorporate attentional processes. Only recently have scholars begun to include attention as a key component in formal choice models (Bordalo, Gennaioli, & Shleifer, 2012; Krajbich, Armel, & Rangel, 2010; S. M. Smith & Krajbich, 2019). Advances in process tracing methods like eye tracking and pupillometry have facilitated the improvement of time resolution in measuring decision processes. Recent insights from increased research efforts using these methods highlighted the role of attention in guiding decisions (e.g., Schulte-Mecklenbeck, Kühberger, & Johnson, 2019). Still, it is not yet entirely clear how attention regulates the decision making process.

A large and growing body of research has already clarified the role of affect in modulating judgments and decisions. For instance, the established affect-as-information mechanism describes the misattribution of affective experiences to unrelated judgments (Schwarz & Clore, 1983). Cai, Yang, Wyer, and Xu (2017) demonstrated that a bitter taste can attenuate the effects of positive mood on spending decisions. In a field experiment in a Chinese supermarket, shoppers in a good mood drinking a bitter beverage showed less impulsive spending behavior afterwards. We know from the classic gambling paradigm that “without affect, information lacks meaning and will not be given weight in decision making” (Bateman, Dent, Peters, Slovic, & Starmer, 2007, p. 376). Though, we do not yet fully understand the affect-motivation link. It is clearly oversimplified to map positive affective states onto motivational approach tendencies, and negative affect onto
avoidance tendencies. For instance, anger and fear are both negative emotional states but anger is associated with approach and fear with avoidance (Lerner & Keltner, 2000).

Finally, one point of contention is the question of multi-process models (e.g., Alós-Ferrer & Strack, 2014; Evans, 2008; Evans & Stanovich, 2013) versus single-process models of judgment and decision making (Krajbich et al., 2010; Kruglanski & Gigerenzer, 2011). The dual-process position holds that decisions arise from the interplay of two processes: one intuitive-associative, processing information quickly, resource-efficiently, and in parallel; the other more analytic, processing information in serial, and relying heavily on cognitive capacity. Advocates of the unified framework argue that such a distinction is not warranted and may in fact lack empirical content in the sense that dual-process theories may not be falsifiable (Keren & Schul, 2009). Over the course of the past years, this dispute has inspired many theoretical and methodological innovations in the field (e.g., Alós-Ferrer, 2018; De Neys & Pennycook, 2019; Krajbich, Bartling, Hare, & Fehr, 2015), and it resulted in highly prolific research activities addressing the cognitive processes that shape human judgments and decisions in various domains.

The present dissertation is set out to address some of the issues outlined above, focusing on one domain of human decision making, that is, economic decisions. Given that most of our thoughts and actions can be construed as series of decisions, it can be doubted whether a universal model of human decision making would be plausible, or even desirable. In light of the variety and ubiquity of decisions in everyday life, it seems natural to venture a more modest approach by seeking to shed light on one domain of decision making at a time. Therefore, the present dissertation concentrates on the investigation of decisions in economic contexts. Even though there is some evidence for a common psychological currency linked to all sorts of decisions (Levy & Glimcher, 2012), it seems appropriate to confine the main research question of the present dissertation to the domain of economic decisions.

This dissertation investigates the impact of distinct motivational and volitional states of mind on decision outcomes and processes in economic contexts. Four experiments address some of the questions outlined above. In more detail, I explore the interactive effects of motivation, volition, and financial incentives on economic decisions (Experiments 1a, 1b) to inform the debate about the impact of multiple sources of
Motivation, and their mutual effects on choices in economic settings. Using eye tracking (Experiments 2, 3), I investigate decision processes in risky choices to investigate how these processes may be affected by motivation and volition. The examination of response times, visual fixations, and pupil diameter seems particularly promising, given our limited understanding of how motivation and volition may shape the cognitive processes in decisions under risk.

The remainder of the present dissertation is organized as follows. In the Theoretical Part, I will first (Chapter 1: Motivation and Volition in Economic Decisions) review the established effects of goals, action plans, and regulatory foci on economic decisions. This chapter provides a starting point for a closer look at experimentally induced motivational and volitional states of mind. This experimental approach, instead of only observing the effects of goals on performance or measuring motivation by self-reports, may prove particularly insightful to foster our understanding of the role of motivation and volition in economic decisions. I will further argue that the underlying cognitive processes are crucial to understanding economic decisions, echoing the call for process tracing methods to scrutinize these processes.

The following chapter on the mindset theory of action phases (Chapter 2: Mindset Theory of Action Phases) reviews the existing work on the deliberative and implemental mindsets, defined as distinct sets of cognitive procedures activated at different stages during goal pursuit. I will focus on studies in which these mindsets were experimentally induced to isolate their distinct cognitive characteristics. Several dissociable features can be identified to distinguish the cognitive procedures activated alongside these mindsets. Since the deliberative and implemental mindsets remain active for some time and carry over to subsequent tasks, the experimental induction of these mindsets may serve to study the unique influences of motivation and volition on economic decisions and their processes.

I will then turn to the role of financial incentives in regulating economic performance and discuss some inconsistencies regarding the widely accepted assumption that incentives increase the effort invested in a task, and thus, improve performance (Chapter 3: Incentives). In doing so, I will capitalize on laboratory and field studies from psychology and economics, which sometimes yield surprisingly different findings.
regarding the effectiveness of financial incentives for improving performance. In the following chapter, I will develop a research program to tackle some of the questions that remained unanswered after consulting the existing literature on motivation, incentives, and economic decisions (Chapter 4: Overview of the Empirical Work). In this chapter, I will explicate a number of hypotheses to be scrutinized in four experimental studies.

The Empirical Part reports on these four experiments. Evidence from behavioral experiments (Experiments 1a, 1b), as well as eye movement and pupil dilation measurements (Experiments 2, 3) informs the debate about the effects of motivation and volition in economic decisions and speaks to some of the questions formulated above. The first two studies (Chapter 5: The Interactive Effects of Mindsets and Incentives) show that financial incentives determine performance in an economic decision task when a performance-based incentive is contrasted with a fixed rate bonus payment (Experiment 1a). Yet, increasing the absolute amount of the performance-based incentive appears ineffective in terms of performance improvements, as demonstrated by the comparison of high versus low financial incentives (Experiment 1b). Notably, preliminary evidence points to an interaction between financial incentives, and motivational and volitional processes in determining performance in an economic decision task.

In Experiment 2 (Chapter 6: Mindset Effects on Decision Processes Under Risk), I report process data from an incentivized lottery choice task which was completed by participants in a motivational (deliberative) or volitional (implemental) mindset. The results indicate that decision processes are influenced by the mindsets, but choices remain unaffected. Based on a surprising finding in Experiment 2, the fourth study (Chapter 7: The Zero Effect in Risky Choices) follows up on an open question regarding the selective attention to specific lottery attributes. Here, I explore zero-outcomes as special types of risky choice attributes and consider their influence on attentional, affective, and motivational processes. I will argue that affect drives selective attention and motivational avoidance in response to zero-outcomes. Finally, I will synthesize the results of all four experiments and attempt a tentative outlook at promising avenues for future research (Chapter 8: General Discussion).
CHAPTER 1

MOTIVATION AND VOLITION IN ECONOMIC DECISIONS

One can think of many ways in which motivational and volitional processes may influence economic decisions. An individual’s motives, e.g., with respect to achievement, affiliation, or power, certainly determine what kind of personal goals individuals seek to pursue, and which strategies they deem appropriate to accomplish these goals (e.g., Atkinson, 1957; McClelland, 1975). Individual differences, for instance, in extraversion or conscientiousness, can also be expected to affect individual goal setting and goal striving. Personality traits certainly have a considerable impact on the many decisions made by individuals in the pursuit of goal-directed action. Whether an individual decides for or against a specific course of action will also depend greatly on the expectation of extrinsic incentives, i.e., the degree to which actions and decisions foreseeably trigger rewards and punishments from external sources. Such extrinsic incentives, like monetary rewards, social feedback on one’s actions, or interpersonal and intrapersonal conflicts, will also shape the way in which individuals act, decide whether to remain persistent in goal striving, or how they think behavior should be modified to accommodate social concerns in the pursuit of personal goals. Finally, when it comes to individual decisions in specific situations, the current motivational or volitional state of the mind may influence decision making, for example, when situationally contingent prior information push individuals toward actions and decisions which, under different circumstances, they would have disapproved of or even wholeheartedly rejected.

It becomes evident that motivational and volitional processes are ubiquitous in human judgment and decision making. However, in economic decision research, the impact of motivation and volition has been unduly neglected. While there is ample research on the role of incentives and goals on decisions in economic contexts, only few studies so far have addressed the questions of how motivation and volition more generally
shape economic decisions, and how these influences may be represented in formal models of economic choice. The lack of research in this area has been acknowledged only recently. For instance, in a current handbook mapping out the state of the art in judgment and decision making research, Wedell (2015, p. 119) noted: “Although there are numerous ways in which motivation and affect may influence the choice task, most formal choice models do not explicitly incorporate these influences. Thus, this is an area for current and future development.”

In particular, there is a gap in the decision research literature concerning the simultaneous consideration of motivation and volition in modulating decision processes like cognitive effort, information search, or affective arousal. That is, there seems to be no work, so far, that examined how motivation and volition, as grounded on a unified theoretical framework, may influence (economic) decision processes. A literature search on the Web of Science (www.webofknowledge.com, Clarivate Analytics, Philadelphia, PA, USA) exemplifies this apparent gap in the literature. Entering “motivation”, “volition” and “decision processes” in the search returned zero publications on this topic.

This is somewhat surprising, considering the rich research traditions in psychology and behavioral economics, on issues related to motivation and willful self-control, i.e., volition. To study the impact of motivation and volition on economic decisions, prior work has mainly focused on the role of goals, action plans, and regulatory foci that express motivational tendencies of approach and avoidance. In the following sections, I will briefly review these studies, pointing to some inconsistencies and emphasizing the apparent gap in the decision research literature. I will conclude this chapter with a call for an approach to study the effects of motivation and volition on economic decisions that is based on a single theoretical framework.

**Goals.** A rich tradition of goal setting research emphasizes the importance of goals for economic performance (Locke & Latham, 2002). Heath, Larrick, and Wu (1999) highlighted the role of goals as reference points in risky choices. Accordingly, decision makers are satisfied when their choice’s outcome is above the reference point, i.e., better than their goal, and then, subsequently, they avoid taking high risks. On the other hand, decision makers are risk seeking so long as their goal is not achieved, or when goal accomplishment is at risk. This was demonstrated, for example, in a study with
professional financial analysts. Hunton, McEwen, and Bhattacharjee (2001) found that the prospect of a future cooperation with a financial forecast firm (i.e., a professional goal) affected the analysts’ risk attitudes. Analysts who believed they would establish an ongoing professional relationship with the forecast firm showed increased risk seeking, relative to other analysts anticipating no future contact with the firm. That is, in this study, the professional cooperation goal promoted risk seeking, consistent with the idea of goals as reference points.

Further evidence for this effect of goals on risk taking comes from experiments in which participants chose between lotteries of varying probabilities and outcomes, expected values, and gains versus loss framing (Larrick, Heath, & Wu, 2009; Lopes & Oden, 1999; Payne, Laughhunn, & Crum, 1980, 1981; Sokolowska, 2006). Yet, Jeffrey, Onay, and Larrick (2010) demonstrated that decision makers faced with risky lottery choices may be risk seeking even in situations in which the outcomes satisfy a specific reference goal with certainty. Specifically, when all outcomes of all choices achieved or exceeded the previously set goal, decision makers started to take higher risks in subsequent choices rather than opting for the less risky option that promised a sure gain.

Other authors looked into the distinct influences of graded performance goals on economic decision. For instance, Schiebener, Wegmann, Pawlikowski, and Brand (2012) investigated the effects of anchoring and setting low versus high performance goals. In this study using a game of dice, participants forecasted one to four digits that would be contained in the next dice throw. Their hypothetical reward was inversely related to the number of proposed digits. That is, the amount to gain (but also the probability of losing) was highest when decision makers predicted only one number to be shown by the next dice throw. The amount was smaller (but the probability of winning was higher) when decision makers decided to forecast combinations of two, three, or four numbers, respectively, which would contain the digit shown by the next dice throw. It appeared that setting high performance goals (in terms of the final amount won in the dice game), unlike low performance goals, were related to more risky choices. When decision makers set low performance goals, they more often forecasted single digits instead of combinations of two, three or four numbers.
Using a slightly modified version of the same game of dice, Schiebener, Wegmann, Pawlikowski, and Brand (2014) found additional support for the notion that high performance goals may lead to increased risk taking and, in consequence, potentially inferior decisions. In this study, the number of dice throws was not restricted so that participants could freely decide when to end the game. Participants who set an explicit performance goal before entering the game made more advantageous decisions than participants in the control group. However, not all types of goals delivered the same benefit; high performance goals, compared to low-to-moderate goals, were associated with more trials played and more risk taking across choices, resulting in comparatively greater negative outcomes overall. These findings demonstrated that explicitly set low-to-moderate performance goals may enhance decisions by favoring reduced risk taking. On the other hand, high performance goals were associated with greater risk seeking and negatively affected overall decision outcomes.

Hassin, Bargh, and Zimmerman (2009) used a version of the Iowa Gambling Task (e.g., Bechara, Damasio, Tranel, & Damasio, 1997) to investigate non-conscious goal pursuit in decisions under risk. In the Iowa Gambling Task, participants pick cards from one of four decks with varying potential gains and losses. Two of the decks promise consistently high expected outcomes and should thus be preferentially selected when these characteristics become apparent. A performance priming procedure manipulated goals: in the high-performance goal condition, participants completed a word-search puzzle containing words relevant to the concept of high performance (e.g., win, ambitious, competition). Participants in the control condition completed a similar puzzle that contained neutral words. In the subsequent gambling task, performance primed individuals were more flexible in adapting to the location of the favorite deck, and thus, demonstrated reduced risk seeking particularly during the last trials (when the location of the favorite deck was highly apparent). Note that in this study, like in all other studies reviewed thus far, participants were paid a fixed rate regardless of their performance in the task. Since there were no financial incentives, their decisions in the Iowa Gambling Task and the other paradigms described above did not have real consequences in terms of individual earnings. I will return to this issue shortly.

As a preliminary conclusion, it can be safely asserted that performance goals influence risk taking, and perhaps economic decision making more generally. Clearly,
decisions and performance may benefit from goal setting. But economic performance is not always aligned with reduced risk seeking. Under certain conditions, higher risks may result in better outcomes on average. Contingent on the task demands, smart risk taking strategies may actually improve performance (see for instance, Rahn, Jaudas, & Achtziger, 2016a). Thus, it is important to keep in mind the characteristics of the task at hand when discussing whether goals per se, or low versus high performance goals more specifically, are instrumental for optimizing economic decisions.

As noted earlier, the above studies on goals and economic decisions did not incentivize choices. Hence, the question remains whether the observed choice preferences and risk seeking patterns generalize to decision environments that are more aligned with real-life decisions outside the laboratory. Realistic choices typically entail some form of incentives, and extrinsic rewards or punishments are important motivators of goal-directed action. As I will discuss in the following chapters, it is important not to disregard this source of motivation and provide monetary incentives when studying the effects of motivational and volitional processes in economic decisions.

Some studies exist that investigated goals in incentivized decisions. For instance, Ben Zur and Breznitz (1981) found that time pressure in incentivized risky choices (i.e., strict time goals) led to reduced risk taking relative to medium or low levels of time pressure (i.e., more relaxed time goals). Additionally, participants under high time pressure spent more time searching for loss-relevant information (probabilities, outcomes of losing option) while participants in the low time pressure condition focused on gains-related information. This preference for gain versus loss information determined choices. That is, when under high time pressure, decision makers were enticed to choose the less risky option in order to relieve the stress induced by the threat of negative consequences. It is plausible to assume that time pressure produces more stress when money is at stake, compared to hypothetical choices. Yet, FeldmanHall, Raio, Kubota, Seiler, and Phelps (2015) found that experimentally induced stress (using the cold pressor task, e.g., McRae et al., 2006) increased the amount of money bet in a gambling task compared to a no-stress control condition. Furthermore, induced stress also reduced the amount of money entrusted to partners in a trust game, indicating that the effects of goal-induced stress experiences may either increase or decrease risk taking under different conditions.
Ballard, Yeo, Neal, and Farrell (2016) used a goal-framing manipulation to investigate decision making in the pursuit of two simultaneous goals (approach and avoidance goal). That means two simultaneous goals were set, one aimed at achieving a target score (approach), the other aimed at avoiding a target score (avoidance). Participants decided which of these goals to prioritize in a sequence of trials. The decision was incentivized: Decision makers could increase their payment by achieving one or both goals (gain framing) but failing one or both goals reduced the payment (loss framing). Goal framing affected decisions of goal prioritization consistent with prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). In the gain frame, decision makers under-prioritized the goal in the worse position but over-prioritized the same goal in loss frame. Hence, decision makers were more risk seeking in loss frame but avoided risks in the gain frame.

Investigating team performance as a function of goal setting in incentivized decisions, Knight, Durham, and Locke (2001) used a multiplayer computer game. These authors compared triad team performance across two conditions of goal difficulty, i.e., difficult versus easy performance goals. In this study, each participant controlled a virtual tank and triad teamwork was required to successfully achieve a (difficult versus easy) target score by attacking on-screen enemy tokens. While the game encouraged risk seeking to attain higher scores, the teams could choose attack strategies with different levels of risk. In both goal conditions, incentives were offered in one of two sessions, so the payment was based on team performance. Across sessions, triads in the difficult goal condition chose riskier strategies and performed better in the game. Incentives interacted with goal difficulty increasing team performance when difficult goals were previously set but not when triads had easy goals.

Taken together, goals may be useful to improve economic performance. But it appears that economic decisions may be differentially influenced by goals under different incentive conditions. This highlights the importance of incentives as motivators of economic decision making. I will return to this issue again in a separate chapter on the role of financial incentives in modulating economic decisions and their processes (Chapter 3: Incentives). But first, a brief consideration of further research that examined motivation and volition in economic decisions is on order.
**Action plans.** Some studies examined self-regulation strategies (i.e., volitional interventions) and their effects on incentivized economic decisions. This was done, for instance, by Thürmer, Weber, and Gollwitzer (2014), who investigated group decisions in a hidden profile paradigm (Stasser & Titus, 1985). In different goal intention conditions, groups either had simple goals (e.g., “I want to find the optimal decision alternative”) or they formed additional if-then plans to support their goal intentions. That is, they furnished their goals with implementation intentions (Gollwitzer, 1999), e.g., “And when we finally take the decision sheet to note our preferred alternative, then we will go over the advantages of the non-preferred alternatives again”. Optimized group decision making was supported by financial incentives. When if-then plans were formed, group decision quality was improved, relative to the simple goal condition.

Investigating individual decision making, Hügelschäfer and Achtziger (2017) found that both goals and implementation intentions, that were formed to support analytical thinking, improved decisions in a Bayesian updating paradigm (Achtziger & Alós-Ferrer, 2014; Charness & Levin, 2005). Hence, if-then action plans had a strong potential to improve economic decisions, although it remained open to further research to corroborate the initial evidence provided by these studies. It remains to be shown whether the beneficial effects of implementation intentions may be generalized to performance in other economic decision tasks as well.

**Regulatory fit.** Another approach to study motivation effects on decision making relies on the traditional distinction between approach and avoidance motivation (e.g., Elliot & Thrash, 2002). Regulatory fit theory (Crowe & Higgins, 1997; Higgins, 1997) describes a prevention focus and a promotion focus that are associated with motivational avoidance and approach tendencies, respectively. With regard to economic decisions, Crowe and Higgins (1997) postulated that the promotion and prevention foci should produce systematic response biases. In fact, when in a promotion focus, decision makers showed a risky (fast) response bias, while decision makers in a prevention focus made more conservative, less risky (slow) choices. Other authors investigated the impact of regulatory foci on the shape of the utility function (Halamish, Liberman, Higgins, & Idson, 2008). Halamish et al. (2008) found that in a prevention focus, uncertainty reduced the perceived intensity of losses more than the perceived intensity of gains. On the other hand, Kluger, Stephan, Ganzach, and Hershkovitz (2004) demonstrated that the
promotion focus lead to a general tendency of overweighing moderate and moderate-to-high probabilities.

Note that these studies on regulatory foci did not incentivize choices. In contrast, Scholer, Zou, Fujita, Stroessner, and Higgins (2010, Study 3) devised a stock investment paradigm, in which decision makers’ earnings were contingent on the outcomes of a simulated stock market. In contrast with the assumption that a prevention focus would produce a conservative response bias, prevention facilitated risky choices under loss conditions. Zou, Scholer, and Higgins (2014) observed in a similar paradigm that decision makers made more risky choices when in a promotion focus as long as prior choices had no effect on the stock portfolio. When experiencing a large gain, however, choice preferences shifted toward the more conservative option. Hence, effects of regulatory foci may depend on the incentivization of the given economic decision task. Further research is required to assess the possible interdependence of regulatory foci and incentives in economic decisions.

**Conclusion.** Taken together, the interplay of motivation, volition, and incentives in economic decisions is rather complex. Motivational (e.g., goals, regulatory foci) and volitional processes (e.g., implementation intentions) impact decisions under risk, but the effects might rely on or interact with incentivization and may vary dramatically across task demands. Risk aversion may also change over time as decision makers get older (Mata, Josef, Samanez-Larkin, & Hertwig, 2011). With regard to motivation over the life span, Pachur, Mata, and Hertwig (2017) suggested a motivational reorientation toward positivity in older adults. Older adults made more risky decisions, presumably because they experienced less negative affect and were less driven to prevent losses. Hence, age may also be an important predictor of motivational processes in relation to risk attitudes and economic decisions.

In conclusion, most studies so far addressed motivation by varying performance goals in economic decision tasks, assessing different strategies of planning how to implement action, or by manipulating approach and avoidance motivation through regulatory foci. There is little work so far that evaluated motivational and volitional processes and their effects on economic decisions beyond goals in a more holistic way, accounting for their differential impact on the basis of a single theoretical framework.
Moreover, there is a lack of studies investigating experimentally induced motivational and volitional states of mind rather than just altering performance goals and action plans for optimizing economic decisions. Experimentally manipulating motivational and volitional processes facilitates a closer look at the differential impact that the distinct cognitive procedures activated by these processes could have. A theoretical framework that invites such a view and facilitates the study of the cognitive characteristics of motivation and volition, and how these could prove relevant for economic decisions, is the mindset theory of action phases (Gollwitzer, 1990, 2012), which I will turn to in the following chapter.
CHAPTER 2

MINDSET THEORY OF ACTION PHASES

The mindset theory of action phases (MAP; Gollwitzer, 1990, 2012; Keller, Bieleke, & Gollwitzer, 2019) describes goal-directed action as a sequence of four consecutive phases, i.e., goal setting (deliberation), goal striving (implementation), action, and evaluation. Individuals must sequentially traverse these phases in order to succeed in attaining their goals. Each action phase focuses on distinct aspects in the pursuit of goals and holds particular demands and challenges to the individual. A distinct set of phase-specific cognitive procedures (mindset) is activated during each phase in order to facilitate performance of the different tasks to be addressed (see also Achtziger & Gollwitzer, 2007, 2018). A schematic representation of the MAP’s sequence of action phases and their tasks is displayed in Figure 1.

An important distinction of the MAP pertains to the difference between motivation and volition. Motivation, on the one hand, is defined by processes of goal setting and evaluation. It “is construed as appraisal of two things in relationship to each other: the incentive value of an event and the probability that it can be attained” (H. Heckhausen, 1977, pp. 284–285). Motivational processes thus assess the desirability (incentive value) and feasibility (attainability) of potential goals based on an individual’s motives (Keller et al., 2019). Volition, on the other hand, is concerned with goal striving and is defined as “the translation of existing goals into action, and specifically, the regulation of these processes” (Achtziger & Gollwitzer, 2018, p. 279). Accordingly, volition describes the will-based planning and execution of goal-directed action (Keller et al., 2019). Hence, motivational and volitional processes fundamentally differ in terms of their roles during goal pursuit.

According to the MAP, all goal-directed action begins with goal setting. The first action phase (pre-decisional phase) describes motivational processes of selecting one or
multiple goals to be pursued from the set of an individual’s wishes and desires. Individuals evaluate the desirability (incentive value; “Is it worthwhile to pursue this goal?”) and the feasibility (attainability; “Can this goal be achieved?”) of potential goals. Regularly, multiple and sometimes conflicting wishes and desires are worth considering, so careful deliberation and weighing the consequences of acting versus non-acting on different goals is vital to determine the best course of action.

**Figure 1.** Schematic representation of action phases and mindsets in the MAP. Adapted from Keller, Bieleke, and Gollwitzer (2019). Mindset theory of action phases and if-then planning (p. 25). In K. Sassenberg and M. L. W. Vlieks (Eds.), *Social psychology in action*. Berlin: Springer.

When a goal is set and an intention was formed to act accordingly, individuals traverse to the second phase (pre-actional phase). In the pre-actional phase, goal implementation is prepared by processes of planning how, when, and where to act. The formation of goal intentions alone sometimes does not suffice to ensure action. A large body of research, and frequent personal experience, demonstrate that it can be difficult for individuals to translate their intentions into action: People often fail to do what they intend to do (Sheeran & Webb, 2016). To bridge the intention-behavior gap and
successfully implement behavioral intentions, a cognitive focus on planning and executing action is required. Furnishing goal intentions with implementation intentions, i.e., behavioral if-then plans, can dramatically increase the likelihood of translating intentions into actions (Gollwitzer, 1999; Gollwitzer & Sheeran, 2006). That is, planning how to achieve a goal facilitates the transition to the next phase, the actional phase.

The primary task during the actional phase then is the regulation of goal-directed behavior. Persistence in goal striving and shielding the goal from temptations or other potentially conflicting goals ensures a smooth execution of goal-directed action. Persistence becomes particularly important because setbacks or a lack of focus can lead to the emergence of action crises (Keller et al., 2019). An action crisis entails reconsiderations of the goal’s desirability and feasibility, reduced focus on implementation-related information, and eventually, disengaging from goal-directed action (V. Brandstätter & Schüler, 2013). To avoid this, individuals in the actional phase focus on information that supports to sustain their chosen course of action and block doubtful or re-evaluative thoughts. A state of mind that has been linked to the actional phase is the experience of flow (Csikszentmihalyi & Csikszentmihalyi, 1988). When in a state of flow, individuals immerse themselves in the task at hand, ignoring potentially disruptive thoughts and incoming information. A state of flow can be considered the ideal manifestation of a strong action mindset (Rahn, 2016).

Finally, once action is terminated, individuals traverse to the post-actional phase and evaluate the consequences of their actions. Evaluation regards the outcome’s consistency with set goals, i.e., whether these goals have been attained, and may be the starting point for further action based on modified goals. Hence, the tasks to be addressed in the post-actional phase are similar to those in the pre-decisional phase in that they are motivational in nature. For the evaluation of an action’s outcomes it is important to weigh the consequences impartially and to deliberate carefully about further steps.

In each action phase, individuals face different tasks and obstacles in the pursuit of their goals. Consider, for example, a person’s desire to go on a vacation in the summer. Several things need to be considered before deciding on a specific course of action. The first decision is whether to travel at all, since staying home would save time and money, but it might not entail the same psychological benefits as, for instance, a trip to another
country. If considering to travel abroad, numerous possible destinations come into question, some more costly than others. It needs to be decided whether to travel alone, with the partner, friends, family, or all of them, and whether the vacation should be spent reading books at the beach, sightseeing in the city, or hiking in the mountains. Any of these alternatives entails different positive and negative consequences that need to be cautiously balanced to ensure a fun summer vacation. The task demands change dramatically as soon as a decision is made upon the vacation options and an intention is formed to act accordingly. If, for instance, planning to go on a ten-day camping trip with the best friends, several preparations must be made. The leave must be organized with the employer, friends will have to be asked to confirm the trip, campsites must be researched, and group activities arranged for ahead of the trip. While planning the trip, it is important to remain persistent and committed to the goal even in the face of implementational obstacles (e.g., no BBQ on the selected campsite, the best friend’s cancellation of the trip, etc.). In these cases, pondering the consequences and re-evaluating all alternative options anew might simply take too long and risk going on the vacation altogether. So, to come closer to the goal of vacationing in the summer, the plans might as well be optimistically appraised and most obstacles are then likely to be overcome eventually (e.g., bring own BBQ, invite other friends to the trip).

The MAP has introduced the idea of mindsets to explain how the cognitive system responds to the distinct demands of the motivational problems of goal setting and evaluation, versus the volitional problems of goal striving and execution of action. The term mindset refers to a specific “cognitive orientation (i.e., the activation of distinct cognitive procedures) that facilitates performance of the task to be addressed in each action phase” (Achtziger & Gollwitzer, 2018, p. 279). That is, mindsets facilitate the cognitive adaptation to the specific task set at hand. When engaging in goal deliberation, the individual must carefully consider multiple, sometimes conflicting wishes and desires. A deliberative mindset supports this process by a broad attentional focus, open-mindedness to new information, and a cognitive tuning toward information that are relevant in terms of the potential goals’ desirability and feasibility (Gollwitzer & Bayer, 1999). When planning a chosen goal’s implementation, individuals must shield this goal from conflicting desires, and remain persistent to surmount implementational obstacles. An implemental mindset supports these processes by a cognitive tuning toward
information which is relevant for the execution of action and increased optimism with regard to success expectancies and goal attainability (Gollwitzer & Bayer, 1999).

The deliberative and implemental mindsets, once activated, stay in place for some time and can affect attention, cognition, and behavior in subsequent tasks, even if these are unrelated to the task that initiated the mindset. That is, mindsets evince a moment of inertia (Keller et al., 2019). Previous work has examined the temporal stability of mindsets and their dynamics when carried over to unrelated tasks (e.g., Rahn, 2016). While mindsets can be expected to fade out over time when being transferred to an unrelated task (Gagné & Lydon, 2001a; Taylor & Gollwitzer, 1995), Rahn (2016) reported no relevant decay of mindsets over the time of a typical laboratory experiment. In fact, one study showed dynamic mindset effects over the time course of an experiment (Rahn et al., 2016a). In this study, participants in an implemental mindset adopted a more risky but also more profitable strategy in the second half of an incentivized ring-toss game, leading to higher profits than in the deliberative mindset and control group. Hence, decision makers benefited from being in an implemental mindset, however, not from the beginning but only later during the task. It is important to note that mindsets should be conceived of as dynamic states of mind rather than fixed on/off states. As such, mindsets might change over time, the cognitive orientations activated alongside should carry over to subsequent tasks that are unrelated to the origin of the mindset, and mindsets may then decay over time.

On a side note, Gollwitzer and Kinney (1989) pointed out that the dynamic nature of mindsets is an important definitory feature that distinguishes mindsets from simple task sets. Task sets are contingent on a specific task at hand and their related cognitive procedures do not necessarily carry over to subsequent unrelated tasks. Hence, demonstrating that the distinct cognitive orientations of the deliberative and the implemental mindset generalize to subsequent tasks supports the idea of dynamic mindsets as defined in the MAP. The dynamic attribute renders mindsets particularly interesting for experimental research because it facilitates a characterization of the unique cognitive orientations in motivational and volitional states of mind based on their downstream influences on attention, cognition, and behavior. Consistent with this idea, Gollwitzer (1990) noted that action phases might sometimes overlap, e.g., when an individual waits for the optimal moment to implement a fully planned out action, she
might consider the pros and cons of a secondary goal, which she has not yet decided whether to pursue.

While it is important to distinguish the mindsets as conceptualized in the MAP from simple task sets, there are also other uses of the term mindset in the psychological literature. The latter may share some of the conceptual features of the deliberative and implemental mindsets as they relate to distinct cognitive orientations. For instance, the term is frequently used to refer to abstract high-level versus concrete low-level construals (Trope & Liberman, 2010), to describe motivational tendencies based on regulatory foci, i.e., promotion versus prevention (Higgins, 1997), or to illustrate differences between a fixed versus a growth mindset thought to support personal development (Dweck, 2006). In this dissertation, I will strictly limit the use of the term mindset to the distinct cognitive orientations described in the MAP. For a comprehensive review of different mindset concepts in the literature, see Wyer and Xu (2010).

A brief distinction of mindsets from construal level and regulatory foci is in order. Level of construal and regulatory foci may be related with the deliberative and implemental mindsets (Rahn, 2016). Construal level theory (Liberman & Trope, 2008; Trope & Liberman, 2010) distinguishes between low-level concrete representations of objects or events and higher level, abstract construals. Rim, Hansen, and Trope (2013) suggested that abstract (vs. concrete) construals lead to a focus on the causes (vs. consequences) of action. When representing the same event, high-level construals lead to a stronger emphasis on why an action is executed, while low-level construal results in representations more centered around questions of how to act and a focus in the immediate consequences of action. The parallel is apparent: The deliberative mindset may favor higher levels of abstraction, which in turn facilitate goal setting prior to choice, while the implemental mindset may favor concrete representations of objects or events in the course of action as it is concerned with questions of where, when, and how to act. While some researchers pointed out this link between mindsets and construal level (e.g., Freitas, Gollwitzer, & Trope, 2004; Rahn, 2016), only few studies to date addressed this question directly (see for instance, Rasso, 2013, for a notable exception).

While perhaps often aligned, the key distinction between mindsets and construal level is that the former can be characterized by their decisional status as they describe
phases of successive goal pursuit. Mindsets are embedded in a broader model of goal-directed action, relating to various motivational and volitional processes. By contrast, abstract versus concrete construals are not associated with any decisional status or motivational orientation as they apply to mental representations of objects and events more generally. Notably, higher level abstract construals are also related to increased physical endurance and stronger self-control intentions (Fujita, Trope, Liberman, & Levin-Sagi, 2006). It seems that under certain conditions abstract high-level construals may strengthen volition. This notion is difficult to explain if one assumes that the implemental mindset, facilitating effective goal striving, should be associated with more concrete low-level representations pertaining to where, when, and how to execute action. Taken together, the relation of mindsets and construal level is not yet fully understood.

Similarly, regulatory foci (prevention vs. promotion; Higgins, 1997) might be related to the deliberative and implemental mindsets. Regulatory fit theory distinguishes between prevention and promotion foci that are associated with motivational tendencies of avoidance and approach, respectively. A prevention focus is concerned with aspects of security, safety, and responsibility, while a promotion focus is primarily concerned with advancement and accomplishment (Crowe & Higgins, 1997). In line with this assumption, Crowe and Higgins (1997) observed that individuals in a prevention focus were more cautious (conservative) in a signal detection task while those in a promotion focus showed a risky response bias. As Rahn (2016, p. 18) pointed out, “the function of regulatory foci is very similar to that of mindsets”, as both attune information processing to the task demands at hand. But again, mindsets are different from regulatory foci in that they relate to a specific decisional status in the phase model.

The concept of implementation intentions (Gollwitzer, 1999) is also different from mindsets, albeit closely related. Implementation intentions are behavioral if-then plans that build on identifying a critical situation and linking a specific behavioral response to it. They are a powerful self-regulation strategy and robustly increase the likelihood of translating intention into action. A meta-analysis of over 90 independent studies confirmed a medium-to-large effect size of implementation intentions on goal attainment ($d = 0.65$; Gollwitzer & Sheeran, 2006), highlighting the “strong effects of simple plans” (Gollwitzer, 1999).
According to Wieber, Türmer, and Gollwitzer (2015), implementation intention benefits for goal attainment are founded on two processes. First, the specified critical situation (the if-part) becomes highly accessible. Second, through a strong associative link between the mental representations of the specified situation and the target behavior (then-part), efficient action initiation is facilitated without requiring further conscious intent. While interventions based on implementation intentions foster volitional processes in a variety of settings (see, e.g., Hagger & Luszczynska, 2013, for a review of implementation intention effects in promoting health behavior), the underlying mechanisms are crucially different from the cognitive procedures activated by the implemental mindset. One study investigated the joint effects of the implemental mindset and implementation intentions (Diefendorff & Lord, 2003). These authors reported that performance in a human resource staffing task (i.e., hiring workers for a hypothetical company) was improved when if-then hiring decision strategies were applied. The strongest effects were obtained when participants were in an implemental mindset and additionally formed implementation intentions. This finding suggested that the goal attainment benefits of if-then plans were independent from the implemental mindset but may well be supported by it.

**Mindset effects on affect, cognition, and behavior**

This section organizes the empirical work on the deliberative and implemental mindsets. I review studies in which these states of mind were experimentally induced to study their effects on attention, cognition, and behavior subsequent tasks. I focus on the deliberative and implemental mindsets since these cognitive orientations encompass the distinction between motivational and volitional states of mind prior to the enactment of goal-directed behavior (i.e., before the execution of action). Some work exists on the characteristics of the actional mindset and the post-actional (evaluation) mindset, see, for instance, McCrea and Vann (2018) or Nenkov and Gollwitzer (2012). Yet, the deliberative and implemental mindsets have attracted substantially greater research interest because they describe the motivational and volitional processes associated with the successful implementation of goal-directed action. Hence, understanding the role of the deliberative and implemental mindsets in facilitating goal setting and regulating goal
striving, respectively, could point toward new approaches to bridge the intention-behavior gap.

The MAP explains various successes and failures to translate behavioral intentions into action in applied settings such as entrepreneurship (McMullen & Kier, 2016; Van Gelderen, Kautonen, & Fink, 2015) or health behavior (Schüz, Wiedemann, Mallach, & Scholz, 2009). Further examples of how the MAP can serve as a theoretical framework for behavioral analysis include its application to explaining the emergence of international armed conflicts (Johnson & Tierney, 2011) or the perception of power in social targets (Magee, 2009). O’Brien and Oyserman (2008) pointed to the relevance of situationally primed mindsets in criminal investigations. These authors suggested that investigators and prosecutors might benefit from a deliberative mindset which allows them to evaluate evidence more objectively. These studies provided valuable insights into the potential fields of application the MAP may be generalized to. Yet, in the following, I will concentrate on the inertia effects of the experimental inductions of the deliberative and implemental mindsets in the laboratory. Given the high level of control over the environment and potentially confounding factors, this approach seems most suitable to isolate the unique qualities of these mindsets.

The carry-over effects of the deliberative and implemental mindsets on attention, cognition, and behavior have been reviewed in earlier work (e.g., Achtziger & Gollwitzer, 2018; Gollwitzer, 2012; Keller et al., 2019; Rahn, 2016). However, these reviews focused on a selection of experimental and field studies to synthesize the mindset effects that were in line with, for instance, open-mindedness or the cognitive tuning hypothesis (see below). To date, a comprehensive review of the effects of the experimental induction of the deliberative and implemental mindsets, based on an exhaustive literature search, is missing. The present chapter addresses this gap in the literature, providing a broad and inclusive analysis of the existing empirical work on the deliberative and implemental mindsets.

The primary objective is to integrate the existing work on experimentally induced mindsets and their downstream effects on subsequent tasks. By including recent studies, and such in more applied settings, I aim to map out the state of the art in mindset research, providing a comprehensive review and a discussion of well-established mindset
characteristics as well as some inconsistencies observed. I begin the review with studies which investigate how mindsets relate to different cognitive procedures, broadly defined. I categorize these studies according to three major themes: Open-mindedness and attentional processes, cognitive tuning toward mindset-congruent information, and biased processes of self-enhancement and optimism. I then proceed to studies which examine mindset effects on mood, persistence, and performance before turning to the literature on mindsets in judgment and decision making more specifically. Finally, I illustrate how mindsets may influence behavior in applied settings, capitalizing on examples from consumer choice and educational science.

**Cognition and attention**

In a seminal study, H. Heckhausen and Gollwitzer (1987) observed that thought contents and short-term memory span differed considerably between individuals who were about to make a decision, and individuals who had just made a decision and were about to implement it. Pre-decisional individuals had a greater memory span and reported more thoughts related to the incentive value of choice options and performance expectancies, while post-decisional (but pre-actional) individuals had more thoughts about the implementation of the chosen option (see also Gollwitzer, Heckhausen, & Ratajczak, 1990). Differences in thought content and memory span suggested that the cognitive system responded to the distinct demands of goal setting versus goal striving by facilitating specific cognitive procedures to support these tasks. Here, I consider related differences in attention and open-mindedness to incoming information, cognitive tuning, and optimistically biased processes.

**Open-mindedness.** The deliberative and implemental mindsets display different characteristics of open-mindedness in terms of receptivity to incoming information. Open-mindedness to information of all kinds is conducive to goal setting because it supports the careful deliberation about potential goals’ desirability, feasibility, and consequences prior to selecting an option and eventually acting on it. It is important to assess this information accurately and realistically before making a choice. In an implemental state of mind, open-mindedness to new information could hinder goal
shielding in the face of temptations or implementational obstacles. Hence, a closed-minded focus on effective goal implementation is conducive to goal striving.

This idea was supported by H. Heckhausen and Gollwitzer’s (1987) study on short-term memory. Participants in a deliberative mindset processed information faster, leading to more correctly recalled information. Gollwitzer and Bayer (1999) demonstrated increased readiness to process peripheral information in a perceptual discrimination task when in a deliberative mindset. A similar pattern was found for incidentally presented information. Participants in a deliberative mindset showed higher receptivity to incidental information compared with implemental mindset participants (Fujita, Gollwitzer, & Oettingen, 2007). As shown in these studies, open-mindedness increased the receptivity to information in two ways; by increasing the speed of information processing and by heightened readiness to process peripheral and incidental information. By contrast, the implemental mindset was associated with reduced ambivalence and conforming more closely to one’s own attitudes, indicating more closed-minded thinking (Henderson, de Liver, & Gollwitzer, 2008).

Further evidence for open-mindedness in terms of a broader attentional focus was reported by Büttner et al. (2014). In this study, deliberative and implemental participants’ breadth of attention differed during scene perception. Participants in a deliberative state of mind scanned the entire scene more evenly, while participants in an implemental mindset focused on foreground objects. Also, Höner (2006) showed increased receptivity to incoming information in an experiment with youth soccer players. Using a within-subjects design in which participants traversed from the deliberative mindset to the implemental mindset, participants viewed realistic soccer scenes from a first-person perspective. They first decided whether they would play a pass to the left or to the right teammate and then indicated how they would do it. That is, participants were in a deliberative mindset first until deciding whom to pass the ball. When they indicated their decision by pressing a button on a foot pad, they traversed to the pre-actional phase, now considering how this action should be implemented. When in a deliberative mindset, participants had a broader attentional focus, as indicated by longer saccades and more deliberative saccades between the alternative options of passing the ball. In the moment of the decision, the relative share of deliberative saccades rapidly declined, marking a steep nonlinear decrease of receptivity to information in the moment of intention.
formation (about 600 ms before the motor action, which indicated the decision by pressing the foot pad).

Other studies demonstrated open-mindedness in more applied settings such as consumer choice. Consumers in a deliberative state of mind were more open to, and more easily persuaded by, social information in the context of personal savings decisions than implemental consumers (Winterich & Nenkov, 2015). Another study showed that auditors who were tasked with checking complex accounting estimates benefited from being in a deliberative mindset (Griffith, Hammersley, Kadous, & Young, 2015). When in a deliberative state of mind, auditors checked the accounts more accurately, considering all relevant information impartially. Compared with auditors in an implemental mindset and a control condition, deliberative auditors were more likely to identify biased estimates as unreasonable and to act on the identified inconsistencies by contacting their superiors. In line with earlier findings (Fujita et al., 2007), the deliberative mindset facilitated the acquisition of incidentally presented information and its incorporation into the analyses. Auditors in a deliberative mindset were more conservative (i.e., critical) when evaluating financial reports, and they were more likely to identify inconsistencies therein, leading to overall increased quality of auditor performance (see also Rasso, 2013, on mindsets and professional skepticism).

Taken together, there is ample evidence for a cognitive shift in open-mindedness when traversing from the deliberative to the implemental mindset. Pre-decisional individuals are more open to considering all available information, including incidental, peripheral, background, and social context information. The attentional breadth abruptly narrows after intention formation and individuals then focus on salient, implementation-related information.

**Cognitive tuning.** A focus on implementation-related information after intention formation, i.e., when in an implemental mindset, can be expected based on the cognitive tuning hypothesis (Gollwitzer & Bayer, 1999). Accordingly, mindsets tune cognitions (thoughts, encoding and retrieval of information) to mindset congruent information. Individuals in a deliberative mindset are tuned to information about potential goals’ desirability and feasibility, while implemental participants focus on information related to when, where, and how implement action.
Early evidence for the cognitive tuning hypothesis comes from two observations. First, spontaneous and cued thought production in the deliberative and implemental mindsets differ with regard to thought content: deliberative participants have more thoughts about the incentive value (e.g., consequences of acting), while implemental participants’ thoughts were more focused on where, when, and how to act (Gollwitzer, Heckhausen, & Steller, 1990, Study 1; H. Heckhausen & Gollwitzer, 1987). Second, recognition memory differs: deliberative participants better recall information about the consequences of acting, implemental participants better recall implementation-related information. That is, the deliberative and implemental mindsets support encoding and retrieval of mindset congruent information. This was shown in a study by Gollwitzer, Heckhausen, and Steller (1990, Study 2; see also Gollwitzer & Bayer, 1999). These authors presented participants with picture slides portraying a person pondering about an unresolved personal issue. A second slide contained a description of the person’s thoughts about positive and negative consequences of acting, as well as her consideration of implementational steps to solve the issue. When asked to recall the information on the slides after a five-minute distraction task, participants in the deliberative mindset better recalled information about the person’s thoughts related to the positive and negative consequences of action, while implemental participants better recalled the implementation-related information (see also Chandran & Morwitz, 2005).

Hiemisch, Ehlers, and Westermann (2002, Study 1) also reported different recognition memory for deliberative and implemental participants in line with the idea of streamlined encoding and retrieval of mindset congruent information. That is, deliberation related information was better recalled in the deliberative mindset condition, while implementation related information was better retrieved from memory in the implemental mindset condition. An interesting additional finding qualified this effect. Examining the role of situational mindsets in social anxiety, the authors observed a reversal of mindsets for socially anxious individuals (Hiemisch et al., 2002, Study 2). When asked to plan a social situation, participants high on social anxiety inappropriately adopted a deliberative mindset, undermining successful implementation of social goals. In contrast, when pondering the pros and cons of social situations, socially anxious participants failed to adopt a deliberative mindset to support effective goal setting.
It has been proposed that the implemental mindset’s cognitive tuning to implementation-related information generalizes to a broader preference for feasibility-related information about expectancies and probabilities (relative to desirability-related information about the incentive value in the deliberative mindset). For instance, Rahn, Jaudas, and Achtziger (2016b) argued that an implemental mindset should be associated with preferential processing of probabilities in a lottery choice task. Given that visual attention captured processing preferences, these authors expected more and longer fixations on the lotteries’ probability attributes in the implemental mindset compared to the deliberative mindset. However, no mindset effect was observed, attention was distributed similarly to information about lotteries’ desirability and feasibility in both mindsets. While this finding seemed upsetting at first view, it may well be the case that a lack of performance-based incentives in this study attenuated the effects of mindsets. Since decisions were hypothetical and without consequences in terms of individual earnings, information search and choice behavior might have remained invariant across the induced deliberative and implemental mindsets because participants were simply not sufficiently motivated to engage in the task. This raises the question whether the cognitive tuning effects in risky choices might rely on difficult (i.e., challenging) tasks with salient incentives (Rahn et al., 2016a, b). I will return to this point in the following chapters.

**Biased processes of self-enhancement and illusory optimism.** Beckmann and Gollwitzer (1987) reported partiality of memory recall for implemental participants. When in an implemental mindset, participants retrieved more information about the chosen alternative than the nonchosen one, indicating that information processing was partial to the chosen option to facilitate its effective implementation. Consistent with this pattern, E. Harmon-Jones and Harmon-Jones (2002) observed that the chosen option was evaluated more positively in the implemental than in the deliberative mindset, supporting the idea of the implemental mindset’s function of shielding the chosen goal from temptations or reconsideration.

The self-protective (and self-enhancing) function of the implemental mindset was also shown in studies on the illusion of control and the optimism bias (Gollwitzer & Kinney, 1989; Taylor & Gollwitzer, 1995). Taylor and Gollwitzer (1995) observed relatively realistic evaluations of the perceived vulnerability to risks in the deliberative mindset, but implemental mindset participants perceived themselves to be less likely than
peers to experience a number of adverse life events in the future (see also Keller & Gollwitzer, 2017). Further evidence for increased (illusionary) optimism in the implemental mindset, versus realistic processing in the deliberative mindset, include optimistic expectations of future performance (Armor & Taylor, 2003; Puca, 2001, 2004), positive illusionary self-evaluations (Bayer & Gollwitzer, 2005), and higher hopes for success (Puca, 2005). Clearly, these general tendencies of the implemental mindset might be moderated by individual differences (e.g., achievement motivation; Puca, 2005) or context variables. For instance, Puca and Slavova (2007) observed that self-evaluations in social comparisons were only optimistically favorable to the self when participants did not expect to compete with the targeted others. If they expected a direct competition, self-evaluations were more modest.

A series of studies on the role of mindsets in thinking about romantic relationships revealed that mindsets also affect partner and relationship perceptions. When in a deliberative mindset, romantic partners’ prediction of their relationship survival was more valid (i.e., more likely to be accurate) than in an implemental mindset (Gagné & Lydon, 2001a; Gagné, Lydon, & Bartz, 2003). In an implemental mindset, partner perceptions were more idealistic when focusing on a non-relationship goal, the deliberative mindset increased idealistic partner perceptions when focusing on a relationship goal (Gagné & Lydon, 2001b). These and other findings of mindset effects in thinking about romantic partners (VanderDrift & Agnew, 2014) support the notion of self-protective goal shielding in the implemental mindset through biased expectations about the partner and the relationship’s future. By contrast, in the deliberative mindset, these perceptions and predictions seemed to be more realistic and impartial, in line with more open-mindedness generally when in a deliberative state of mind.

**Mood**

One could expect optimistically biased processes of self-protection or self-enhancement in the implemental mindset to entail a positive affective experience. But the effects of mindset on affect, and on mood in particular, are less clear. Some studies observed better mood in the implemental mindset compared with the deliberative mindset (V. Brandstätter, Giesinger, Job, & Frank, 2015; Taylor & Gollwitzer, 1995), while others
failed to replicate this pattern (Büttner et al., 2014; Fujita et al., 2007) or resulted in inconsistent evidence within a series of interrelated studies (V. Brandstätter & Frank, 2002). Yet other studies reported positive affect based on increased approach motivation observed in the implemental mindset (C. Harmon-Jones, Schmeichel, Mennitt, & Harmon-Jones, 2011; E. Harmon-Jones, Harmon-Jones, Fearn, Sigelman, & Johnson, 2008). Thus, mood may be raised if approach motivation is induced by the implemental mindset. However, approach motivation may also be linked to negative affect (e.g., anger), so the valence and intensity of mindset-induced affect likely depend on the specific eliciting context. Better mood in the implemental mindset might occur for approach-oriented positive emotional states like happiness or surprise, but approach motivation linked to anger would certainly not raise any participant’s mood.

The same is true for the deliberative mindset. Prolonged deliberation triggers rumination, which was shown to negatively affect mood (Gieselmann, Ophey, de Jong-Meyer, & Pietrowsky, 2012; Thomsen, Yung Mehlsen, Christensen, & Zachariae, 2003). But note that cross-cultural work suggested that deliberative mindset thought contents may also be rather positive and aspirational when higher level social consequences were considered (which was more likely in the social-oriented United Arab Emirates, compared with the individualistic US society; von Suchodoletz, Rahn, Nadyukova, Barza, & Achtziger, 2019). Thinking about higher level social aspirations when considering potential goals may well lead to better mood. As Gollwitzer, Heckhausen, and Steller (1990, pp. 1125–1126) noted, “the implemental mind-set cannot generally be assumed to produce a better mood than the deliberative mind-set. Planning may be as difficult and painful as deliberating; it all depends on the issue at hand”. It may also be the case that other demands of the experimental task (e.g., positive and negative feedback, or the prospect of attractive rewards) interfere with mood ratings. Hence, mindset effects on mood may differ considerably across demand characteristics of the experimental task, mindset induction procedures, and cultural context.

**Persistence and performance**

Armor and Taylor (2003) reported that the implemental mindset increased performance in a scavenger hunt experiment: implemental participants found 25% more
items than participants in a deliberative mindset. Examining computer game players’ performance, Kosa (2016) found that gamers in an implemental mindset scored significantly higher. They also better predicted their scores. Consistent with these findings, Brandstätter and Frank (2002) showed higher persistence in problem-solving tasks for implemental participants. This was further supported by process data demonstrating more and longer fixations in a lottery choice task when decision makers were in an implemental state of mind (relative to the deliberative mindset and a control condition; Rahn et al., 2016b). But note that in the latter study, decisions were not affected by mindsets. This suggested that implemental mindset participants were more persistent and invested more effort in the task, but deliberative participants were more efficient. They arrived at the same choices investing less effort.

Brandstätter, Giesinger, Job, and Frank (2015, Study 2) reported that implemental participants made shorter time predictions on the task to return a questionnaire about an interpersonal problem within a two-week deadline and, in fact, they returned the report earlier than participants in a deliberative mindset (see also Pösl, 1994; Tu & Soman, 2014, on expedited task initiation when in an implemental mindset). Interestingly, time predictions in the study by V. Brandstätter et al. (2015) did not differ when participants in both mindsets were incentivized to return the report as early as possible (i.e., the value of a book token promised for timely return decreased by €1 for every day into the two-week period). When early task completion was incentivized, both deliberative and implemental mindset participants made equally short time predictions, and both actually returned the report earlier. This finding pointed to an interaction of mindsets and monetary rewards, suggesting that the implemental mindset (relative to the deliberative mindset) expedited time predictions and task completion only when motivation was low.

Other work indicated that the implemental mindset can serve as a performance buffer for individuals with low socio-economic status (SES; Dennehy, Ben-Zeev, & Tanigawa, 2014). Typically found to underperform under threat of stereotype, low-SES individuals performed just as well in a threatening mental arithmetic task as did their high-SES counterparts when in an implemental mindset (but not when in a deliberative mindset).
Taken together, the empirical evidence indicates that performance may be increased in the implemental mindset when individuals are highly intrinsically motivated (like computer game players; Kosa, 2016) or when performance is not linked to payment (V. Brandstätter et al., 2015). But mindset effects on performance occur inconsistently (for instance, Puca, 2001, 2004; Rahn et al., 2016b, did not observe mindset effects on performance) and can be expected to be qualified by other determinants like the quality and quantity of the incentive. Little is known so far about the relation of mindsets and financial incentives. Only very few studies examined the potential interactions, as pointed out by Brandstätter et al. (2015). While the experimental task was incentivized in some studies (e.g., Li, Hügelschäfer, & Achtziger, 2019; Rahn et al., 2016a), there seems to be no study to date that included an experimental variation of financial incentives (e.g., high vs. low, performance-based vs. fixed rate) to test for potential interactive effects of mindsets and incentives.

**Judgment and decision making**

Hügelschäfer and Achtziger (2014) assessed the effects of mindsets on overconfidence, anchoring, and risk aversion, considering gender as a potential moderator. The results indicated that females benefited from being in an implemental mindset by making more realistic confidence judgments. They were underconfident in the deliberative mindset, while males were already overconfident in the deliberative mindset and even more so in the implemental mindset. With regard to anchoring, males but not females were susceptible to irrelevant anchors, i.e., males made more anchor-consistent judgments. Females were also more risk averse in the deliberative mindset relative to the implemental mindset, while the opposite was true for males. These findings highlighted gender as an important moderator of mindset effects on judgment and decision making.

Further studies investigated risk attitudes in relation to the deliberative and implemental mindsets. Keller and Gollwitzer (2017) asked participants to rate the likelihood of negative life events for themselves personally and for peers. In line with earlier work, implemental participants perceived themselves to be less likely than peers to experience negative life events in the future (see also Taylor & Gollwitzer, 1995). In a
second study using an incentivized balloon analogue risk task (Lejuez, Aklin, Zvolensky, & Pedulla, 2003), Keller and Gollwitzer (2017) found less risk-seeking in the deliberative mindset, relative to the implemental mindset and a control condition. Similarly, Rahn et al. (2016a) investigated mindset effects on risk-taking in an incentivized ring toss task (Atkinson & Litwin, 1960). Successful hits were rewarded higher with increased distance from the peg (participants chose the distance in each round). The implemental mindset, compared to the deliberative mindset and a control condition, resulted in more risk-taking over time and resulted in higher payoffs. Li, Hügelschäfer, and Achtziger (2019) examined the effects of the deliberative and implemental mindsets on rational decision making in a Bayesian updating task (Achtziger & Alós-Ferrer, 2014; Charness & Levin, 2005). These authors found fewer reinforcement errors in the implemental mindset, compared to the deliberative mindset, a neutral mindset, and a control condition. These studies provided initial evidence for the idea that an implemental mindset can improve decisions. Increased achievement motivation (V. Brandstätter & Frank, 2002; Rahn et al., 2016b) and learning to take smart risks (Rahn et al., 2016a) may result in better performance in decision tasks.

**Mindsets in applied settings**

Many studies have shown how mindsets affected cognition and behavior in more applied settings and outside the laboratory. For instance, being in a deliberative mindset prior to going to bed reduced the subjective sleep quality for state-oriented (rumination) individuals in a deliberative mindset but not for action-oriented (change promotion) individuals in an implemental mindset (Gieselmann et al., 2012). The fact that a deliberative mindset may be associated with poor sleep quality highlights the ubiquity of mindset effects in everyday behavior. Here, I consider mindset effects in two other areas of importance in everyday life, namely consumer choice and educational settings.

**Consumer choice.** A host of studies exist that examined how the deliberative and implemental mindsets would affect consumer choice in general and shopping behavior in particular. For instance, Büttner, Florack, and Göritz (2013, Study 4) tested the hypothesis of matching effects of chronic shopping orientation (task-focused vs. experiential) and the deliberative and implemental mindsets. The results indicated a fit between shopping
orientation and mindset: task-focused shoppers were willing to pay a higher price when in an implemental mindset; experiential shoppers were willing to pay a higher price when in a deliberative mindset. Spears, Amos, and Yazdanparast (2016) demonstrated another mindset matching effect in consumer choice. When trait planning orientation (planner vs. reactor) was aligned with mindsets, consumers had higher shopping intentions and actually visited more stores. Planners, on the one hand, engage in careful deliberation about the pros and cons of a shopping decision prior to purchase. Reactors, on the other hand, rather spontaneously move ahead on opportunities to implement buying intentions. Accordingly, consumers who described themselves as planners visited more stores when in a deliberative mindset. By contrast, consumers who described themselves as reactors visited more stores when in an implemental state of mind. Other studies showed a more general increase of buying intentions and spending in the implemental mindset relative to the deliberative mindset (Dhar, Huber, & Khan, 2007).

Chandran and Morwitz (2005) investigated how mindsets modulated consumer responses to participative pricing mechanisms in which consumers were involved in determining the price for certain products. These authors argued that shopping intentions were higher for consumers with high perceptions of control over the shopping situation, because the participative pricing scheme facilitated an implemental mindset, while low perceived control consumers remained in a deliberative mindset. Consistent with this argument, high perceived control participants better recalled implemental mindset congruent information, i.e., feasibility-related information regarding when, where and how to conduct a purchase.

As mentioned above, Winterich and Nenkov (2015) showed that consumers in a deliberative state of mind (relative to the implemental mindset) were more open to considering social information when making personal savings decisions. In a related study, Nenkov (2012) observed that consumers in a deliberative mindset were more likely to be persuaded by messages (i.e., advertisements) in a psychological distance framing (e.g., focusing on the future or socially distant persons), while consumers in an implemental mindset were more likely to be persuaded by messages with psychological proximity framing (e.g., focusing on the present or close others). These results linked the deliberative and implemental mindsets to different levels of construal (Trope & Liberman, 2010), indicating a cognitive tuning toward abstract, higher-level aspects of
action (“why”) in the deliberative mindset, and toward concrete, lower-level construals (“how”) in the implemental mindset. However, it should be noted that this mapping may not always apply and that the deliberative and implemental mindsets fundamentally differ from abstract versus concrete construals (see above).

Tu and Soman (2014, Study 5) investigated the impact of the deliberative and implemental mindsets on the categorization of events in time and downstream task initiation. It was shown that consumers categorized future events into events that are like or unlike the present. Task initiation was expedited when an event’s deadline was categorized as like-the-present. The authors proposed that consumers were more likely to approach a task when its deadline was like-the-present because they more readily adopted an implemental mindset. Consistent with this argument, the effect of time categorization on task initiation disappeared when either a deliberative mindset or an implemental mindset was induced.

**Education.** Other studies pointed to the importance of the deliberative and implemental mindsets in educational settings. Mindsets may affect the students’ persistence in academic tasks (V. Brandstätter & Frank, 2002) or their motivation to learn (von Suchodoletz et al., 2019). Mindsets could also help to cope with stereotype threat in everyday classroom situations (Dennehy et al., 2014).

From the instructor’s perspective, mindsets may affect teaching directly. Weinhuber, Lachner, Leuders, and Nückles (2019) showed that situationally primed teacher mindsets influenced classroom teaching. When teaching mathematics, it is important to provide principled information about formal concepts and the logic of mathematical reasoning to facilitate the acquisition of transferable knowledge. In many classrooms, however, teachers focus on explanations how to apply problem-specific procedures rather than explaining the rationale behind a given solution. Weinhuber et al. (2019) argued that math teachers’ tendency to rely on procedure-oriented instead of principle-oriented explanations may be founded on situationally contingent teacher mindsets activated by their everyday classroom interactions with students who were more interested in memorizing step-wise procedures rather than understanding why this particular solution should be applied. To test the idea that math teacher’s explanations were situationally contingent (and thus variable), preservice and experienced teachers
were presented different comics designed to prime a deliberative versus implemental mindset prior to drafting explanations for a math problem. Teachers in an implemental mindset produced more procedure-oriented explanations, describing the steps required to solve the problem. These results suggest that mathematics instructions may benefit from a deliberative teacher mindset shifting the focus to more principle-oriented explanations.

Von Suchodoletz et al. (2019) investigated how mindsets influenced students’ academic motivation in a higher education context. College students from the United Arab Emirates (UAE) and the US self-reported on their attitudes, values, and goals related to learning. When in a deliberative mindset, US students’ motivation to learn was reduced while no such effect was found for UAE students. The authors interpreted this finding in terms of cultural differences in deliberative mindset thought content and achievement motivation. Students from the individualistic, personal achievement centered US society may have suffered from being in a deliberative state of mind because this induced rumination about failure and presumably reduced the participants’ academic self-efficacy. By contrast, in the more socially oriented UAE, students’ deliberative mindset thoughts may have focused on higher order social goals not inducing similar degrees of fear of failure, and thus, facilitating sustained high levels of motivation to learn.

**Summary, conclusion, and directions for future research**

Mindsets have versatile and complex effects on attention, cognition, and behavior in subsequent tasks, even if these are unrelated to the thoughts that initiated the mindset. Both the deliberative and the implemental mindset may be beneficial for the task at hand in some cases but detrimental to performance in others. In this section, I summarize the results of the literature review and discuss the inconsistencies observed in the empirical evidence. I then briefly consider implications of the review for the study of motivation and volition based on the deliberative and implemental mindsets, and finally, I conclude with a tentative outlook on promising areas of future mindset research.
Summary and conclusion

Each potentially beneficial quality of the deliberative and implemental mindsets may prove detrimental to performance in other situations, or affect people differently based on their personality or other moderating factors. Increased open-mindedness and accuracy in evaluations of desirability, feasibility, and the self, which are conducive to successful goal setting, may also support performance in tasks in which exhaustive information search and careful weighing of competing evidence is crucial. In contrast, an implemental mindset might unduly rush decisions in such tasks and increase the susceptibility to biases evoked by salient information. Yet, tasks that require quick responses or increased persistence in the face of implementational obstacles may benefit from an implemental mindset. In these tasks, a deliberative mindset could slow down responses, encourage the re-evaluation of alternative choice options, result in lower goal commitment, and may eventually even lead to an action crisis and disengagement from the task.

Among the best documented effects of the deliberative and implemental mindsets are their distinct qualities in terms of open-mindedness to incoming information, cognitive tuning to mindset congruent information, and biased processes of self-protection and optimism. Given that mindsets are defined as cognitive orientations, it is not surprising that their influences on thoughts and properties of encoding and retrieval of information are so well established. The picture of mindset effects on other dimensions, such as affect, performance, or decision making is less clear. Inconsistencies in these domains are likely based on the diverse demand characteristics of experimental tasks, including design aspects like feedback or meaningful rewards. It can be expected that affective experiences and performance during any given experimental task are highly variable across different combinations of these and other situational context factors (see also Gagné & Lydon, 2001a, 2001b).

In addition, the traditional mindset induction procedure (e.g., Gollwitzer & Kinney, 1989) prompts individuals to think about a personal concern of their own choosing, further increasing the variability of affective experiences related to the induced mindsets and rendering it rather difficult to disentangle the unique contributions of cognitive orientations and context to the experienced affect in subsequent tasks. In fact,
there are various approaches to experimentally induce the deliberative and implemental mindset, although many recent studies rely on the traditional procedure developed by Gollwitzer and Kinney (1989; see also Hügelschäfer & Achtziger, 2014; von Suchodoletz et al., 2019). To induce a deliberative mindset, participants are asked to ponder the pros and cons of acting versus not acting on a self-chosen personal project that has been on their minds for some time, but they have not yet decided whether to pursue it or not. They are asked to consider the positive and negative short-term and long-term consequences of acting and non-acting on this issue, and to rate the likelihood of occurrence for each indicated consequence. The implemental mindset induction procedure has participants plan steps of action to implement a self-chosen goal of personal relevance that they have decided to pursue but not yet taken an action. In this task, participants indicate where, when, and how they intend to act according to each of up to seven action steps.

While thinking about a self-chosen personal concern or project presumably enhances the participants’ immersion in the task and may evoke a stronger mindset, other procedures have been applied to reduce the variability of mindset thought contents on the individual level. For instance, Weinhuber et al. (2019) used standardized comics based on everyday classroom situations all surveyed teachers could easily identify with. Rahn (2016; see also Rahn et al., 2016a) developed an induction procedure that was based on weighing the arguments for and against a proposed law that would require all cyclists to wear helmets. Participants in the deliberative mindset condition rated the strength of several pro and contra arguments before they wrote down the most convincing ones for and against the proposed law, adding new arguments at will. This procedure ensured careful weighing of evidence for both sides. In the implemental mindset condition, participants, after rating the arguments’ strength, were asked to make a final decision for or against the law and write down the most important reasons for their decision. In doing so, participants rationalized their choice, evoking a post-decisional implemental mindset.

These induction procedures can be administered via paper-and-pencil questionnaire booklets or in computerized form for laboratory and online data collection. Although no study so far addressed the systematic differences between mindset induction
procedures, or the differences between field, lab and web-based mindset inductions, the mindsets were already successfully induced using all three approaches. Typically, the successful induction of deliberative and implemental mindsets is evaluated by means of several manipulation checks. These may include, but are certainly not limited to, self-report measures of goal commitment and determination to act, on which implemental participants are expected to score significantly higher due to their post-decisional status (see also V. Brandstätter & Frank, 2002; Rahn, 2016, p. 29).

Although most mindset studies follow a between-subjects design, notable exceptions considered the temporal sequence of the deliberative and implemental mindset as they examined the succession from the pre-decisional to the pre-actional phase in a within-subjects design (Hönner, 2006; Puca & Schmalt, 2001). Using process data from an eye tracking experiment, Hönner (2006) provided compelling evidence for the idea of an abrupt attentional and cognitive shift when traversing from the deliberative mindset to the implemental mindset.

Mindset effects may vary across individuals according to several individual differences (Bayer & Gollwitzer, 2005; Puca & Schmalt, 2001). Gender is an important moderator, as shown in the experiment by Hügelschäfer and Achtziger (2014). While the direction and magnitude of mindset effects may be similar for both females and males, the overconfidence example illustrates that it is important to consider gender as a moderator. Females are typically less (over-) confident than their male counterparts, for instance, when making investment decisions (Barber & Odean, 2001) or in management contexts (Willoh, 2019). Hügelschäfer and Achtziger (2014) observed that males were overconfident regarding their performance in a general knowledge test in the deliberative mindset.

A noteworthy exception is a study by Dederichs (2017), who conducted a large online experiment (N = 452) comparing the traditional induction procedure developed by Kinney and Gollwitzer (1989), the bicycle helmet procedure (Rahn, 2016), and a third one developed for this study, on several dimensions of task performance. The deliberative and implemental mindsets, as instigated by these different induction procedures, differed considerably in terms of their impact on overconfidence, mood, vulnerability to risks, social comparison, and cheating behavior in a general knowledge test. This suggested that different procedures of mindset induction may indeed trigger unique mindset effects, an aspect which certainly merits further consideration.
mindset and even more so in the implemental mindset. For females, the implemental mindset increased confidence ratings, too. But since females were underconfident in the deliberative mindset, their confidence judgments in the implemental mindset more closely matched their actual performance, and thus, were more realistic. Hence, males suffered from increased overconfidence in the implemental mindset, while females benefited from higher confidence resulting in a more realistic appraisal of their own skills.

Other moderators include individual differences in self-evaluation (Bayer & Gollwitzer, 2005), achievement motivation (Puca & Schmalt, 2001), chronic shopping orientation (Büttner et al., 2013), and social anxiety (Hiemisch et al., 2002). Individuals high versus low in social anxiety responded differently to mindset inductions prior to thinking about social situations. Individuals low in social anxiety showed the classic mindset effects of preferential processing of mindset congruent information, while highly socially anxious individuals failed to adopt the appropriate mindset in deliberating or planning to engage in social situations (Hiemisch et al., 2002). Puca and Schmalt (2001) found that individuals motivated by success, but not failure-oriented individuals, benefited from an implemental mindset in complex signal detection tasks. Consistent with other work reporting increased persistence and effort in the implemental mindset (V. Brandstätter & Frank, 2002; Rahn et al., 2016b), this finding highlights the role of optimistic success expectancies in bolstering achievement motivation during goal striving. It also emphasizes the importance of identifying relevant moderators and clarifying the role of gender in moderating mindset effects.

Directions for future research

Several questions remain unanswered regarding the role of financial incentives and other sources of motivation in modulating mindset effects. Achtziger and Alós-Ferrer (2014) observed that providing higher incentives (18 cents vs. 9 cents per correct response) did increase performance in a Bayesian updating task, but the effect was very small and higher incentives did not directly influence error rates or reaction times in the task, indicating no increased effort due to higher incentives. Using the same paradigm in a mindset study, Li et al. (2019) reported notable mindset effects. The implemental mindset was associated with fewer reinforcement heuristic errors, compared with a deliberative mindset, a neutral mindset and a baseline condition. Decision makers
benefited from being in an implemental mindset and performed better in the task, consequently earning more money. Hence, mindsets may under certain conditions produce strong effects on task performance and may sometimes even have surprisingly stronger impact on economic decisions than financial incentives (e.g., Li et al., 2019). Future research should consider the interactive effects of mindsets and incentives. This would be particularly interesting with regard to economic decisions that involve real consequences. I will return to this issue in the Empirical Part, submitting the possibility of an interaction between the deliberative and implemental mindsets to empirical scrutiny.

A second question regards the reliance of mindsets on automatic and controlled decision processes. It was shown that implementation intentions rely heavily on processes automatically cued by an encountered critical situation (Gollwitzer, 1999). To a lesser extent, this might also be the case for the implemental mindset. Clearly, planning the implementation and execution of action involves thoughtful consideration of where, when, and how to act. But a focus on implementation-related information and a narrow attentional breadth could also increase the susceptibility to biased information processing. Individuals in an implemental mindset, being more closed-minded, might rely more heavily on fast automatic processes that can lead to suboptimal decisions (Hügelschäfer & Achtziger, 2014). By contrast, impartial information processing and open-mindedness in the deliberative mindset might involve slower sequential processing. Rahn (2016) pointed out that information processing in the deliberative and implemental mindset might relate to different patterns of relying on fast automatic versus slow controlled decision processes (Alós-Ferrer & Strack, 2014; Evans, 2008). This link between mindsets and dual process models has not yet received much attention (but see Hügelschäfer & Achtziger, 2014; Li et al., 2019) and certainly merits further consideration.

The deliberative and implemental mindsets could also prove useful as readily available, relatively unobtrusive interventions to foster motivational and volitional processes supporting specific (desired) target behaviors. One could think of several examples in which a deliberative mindset could improve performance in complex tasks that require diligent weighing of evidence and thorough consideration of all available alternatives. Auditors checking accounting reports (Griffith et al., 2015) or criminal investigators (O’Brien & Oyserman, 2008) could benefit greatly from being in a
deliberative mindset. Other applications are conceivable in the managerial or medical decision making context. Consider, for example, a manager entrusted with assembling a team for an important company project. If in a deliberative state of mind prior to selecting team members and assigning tasks, she may arrive at a less overconfident, more realistic judgment of her own skills, potentially resulting in optimized task assignments and improved team performance. A physician evaluating the pros and cons of a complicated surgery may make a better-informed decision when in a deliberative mindset. Similarly, the implemental mindset could boost performance in tasks for which intrinsic motivation is high (Kosa, 2016), or support persistence in task completion (V. Brandstätter & Frank, 2002) and optimize economic decision (Li et al., 2019). This could be of particular importance during long-term managerial projects that might seem inviable in the short run but promise higher profits later on. Hence, the deliberative and implemental mindsets open interesting avenues for developing interventions to promote desirable behavior in a variety of real-life decision making domains.
Incentives are important in economic contexts, for example, as motivators in the workplace (e.g., Gerhart & Fang, 2015; Kosfeld, Neckermann, & Yang, 2017). In economics, it is usually assumed that providing financial incentives increases the effort invested in a task, and that increased effort is positively related to task performance. But research on the interplay of financial incentives and other sources of motivation shows that the effect of incentives on performance is not always linear, in the sense that more is not always better. Providing incentives may sometimes have no effect on performance, or even be detrimental to it. Hence, the picture of incentive effects is rather complex and the relation of incentives and performance in economic decisions deserves a closer look.

This section briefly discusses the role of financial incentives in economic decisions. Notably, research in psychology and economics rely on different assumptions about the role of incentives for performance. In economics, incentives are widely regarded as an important determinant of task performance, if not the most important one. It is conventionally assumed that incentives monotonically increase task motivation and thus performance. Hence, it is a tradition and common practice in economics that all experiments include some form of incentive system (e.g., Hertwig & Ortmann, 2001). By contrast, psychological research sometimes assumes that incentives may backfire because they could undermine intrinsic motivation. Intrinsic motivation is assumed to be of crucial importance to foster task performance. Therefore, it is important to consider the impact of extrinsic incentives on other sources of motivation, particularly in situations in which intrinsic motivation is initially high. Furthermore, performance-contingent financial incentives may sometimes not be viable in certain experimental settings or even seem undesirable, e.g., when the behavior in question is primarily socially motivated, rather than relying primarily on the expectation of monetary rewards. These different
assumptions about the effects of incentives in psychology and economics are partly owed to the specific behavior under investigation but also express a less conservative stance among psychologists regarding the importance of using incentives in laboratory experiments.

**Incentives and economic performance**

One key argument from economics in favor of incentivizing the behavior under investigation in experiments, and to use monetary rewards to do so, is founded on the fact that most economic research tests economic theory. Standard economic theory provides a comparatively unified framework built on assumptions of maximization (of utility, revenue, etc.) and defines the standards of optimal behavior to achieve this maximization goal. In order to mirror real-life economic decisions in the laboratory, incentivization is thus a crucial precondition of any experimental design in behavioral economics (Hertwig & Ortmann, 2001). Furthermore, assuming that most people want more money and that there is no saturation over the course of one or multiple experiments, offering financial incentives in the form of monetary rewards provides the best possible incentive mechanism, simply because financial incentives are easier to implement than other forms of incentives (Hertwig & Ortmann, 2001).

Usually, economists insist that performance-based monetary rewards are necessary to increase the effort invested in a task, and thus, to optimize economic decisions and performance. Some evidence from the laboratory and the field supports this claim (Burgess, Propper, Ratto, Kessler Scholder, & Tominey, 2010; Knight et al., 2001). For instance, Burgess and colleagues (2010) demonstrated that financial incentives increased team performance in a long-term field experiment in a UK government agency. Incentives increased individual productivity but also affected the managers’ assignment of team members toward incentivized versus non-incentivized tasks. The latter seemed to bear greater importance for improving team performance: While incentives did affect individual performance, the re-allocation of more efficiently working team members toward incentivized tasks was the more important contributor to the overall increase of team performance. Hence, team performance was mainly increased due to the incentive
effect on smart task assignment decisions made by the management, rather than by its direct effect on the individual team members’ performance.

But incentives may also be beneficial for performance on the individual level. For instance, offering financial incentives increased the effort invested in an IQ test and thereby boosted IQ test performance (Duckworth, Quinn, Lynam, Loeber, & Southamer-Loeber, 2011; but see Gneezy & Rustichini, 2000b, reporting detrimental effects of small incentives on IQ test performance). Similarly, students who received performance-contingent monetary rewards for math and English language tests outperformed their peers who received a fixed payment regardless of their performance in these tests (Hendijani, Bischak, Arvai, & Dugar, 2016).

Further evidence supports the assumption that providing financial incentives moves decisions “closer to the theorist’s optimum and results in a reduction in the variance of decision error” (V. L. Smith & Walker, 1993, p. 260; Camerer & Hogarth, 1999; but see Wilcox, 1993, arguing that incentive effects on error variance are negligible). For instance, incentives may reduce framing effects (Levin, Chapman, & Johnson, 1988) and increase the accuracy of responses in a probability matching task (Hogarth, Gibbs, McKenzie, & Marquis, 1991).

Many economists also argue that even if financial incentives fail to enhance performance, they at least have no negative consequences. There are some exceptions from this conventional economic perspective. For instance, financial incentives may impair performance when people exert too much effort on a task (choking under pressure; Baumeister, 1984). Arkes, Dawes, and Christensen (1986) found that when financial incentives were offered for increased effort, a simple prediction formula (known to be accurate 70% of the time) was neglected and participants tried to outwit that formula. This extra effort led to more errors than were made by those not compensated based on their performance in the prediction task. Similarly, Condry (1977) reported that individuals seemed to work harder when being incentivized; however, the output of that effort was of lower quality compared with the output produced by individuals who were not offered the same incentive for their performance.

In contrast to the classic economic perspective, psychologists often argue that performance-based incentives may actually reduce task performance (e.g., Deci et al.,
This argument rests on the traditional distinction between different sources of motivation, as set forth in self-determination theory (SDT; Ryan & Deci, 2000). The SDT distinguishes between the natural drive to seek new opportunities, supported by the interest in and enjoyment of the task itself (intrinsic motivation), and external sources such as monetary or non-material rewards (extrinsic motivation). According to the SDT, extrinsic rewards (e.g., financial incentives or punishments) may, in some situations, undermine intrinsic motivation and thereby reduce task performance (e.g., Cerasoli, Nicklin, & Ford, 2014; Deci et al., 1999; Eisenberger & Cameron, 1996).

For example, motivation crowding out theory (Frey, 1997; Frey & Jegen, 2001) describes how intrinsic motivation may be reduced by offering extrinsic rewards for tasks in which intrinsic motivation is originally high. In these situations, incentives may oust intrinsic motivation and thereby adversely affect task performance. In a seminal study on the related overjustification effect, Lepper, Greene, and Nisbett (1973) observed that children engaged less in an interesting activity (playing with magic markers) when they expected an extrinsic reward (a certificate with seal and ribbon), compared to children who received the reward without prior expectation. In consequence, children who expected to receive a reward spent less time and invested less effort when playing with the markers, resulting in paintings of inferior quality, as rated by blind judges.

Crowding out of intrinsic motivation may also occur when the behavior in question is motivated by social considerations, such as fairness, reciprocity, or the improvement of one’s self-image (Fehr & Falk, 2002). Consider, for example, the public goods game (e.g., Fischbacher, Gächter, & Fehr, 2001), in which decision makers face a trade-off between private and shared income. In this game, increasing the private income reduces the shared income of the group. While all decision makers in the public goods game will receive a higher income if everyone contributes to the public good, each decision maker has an individual incentive to opt for a higher private income at the cost of reducing the shared group income. Reeson and Tisdell (2008) found that introducing an extrinsic incentive (in the form of a rule that mandates a minimum contribution to the public good) significantly reduced voluntary contributions to the shared group income. Hence, the extrinsic incentive crowded out socially motivated voluntary contributions to the public good.
A similar observation was made in an experiment in which decision makers were asked to contribute to a charity of their own choosing, rather than contributing to a group income to be shared among anonymous group members (Eckel, Grossman, & Johnston, 2005). In this study, a mandatory minimum contribution to the charity was either framed as being provided by the experimenters or framed as a tax on the decision makers’ initial endowment. That is, participants in the first framing condition were told that they could freely choose an optional amount of money from their endowment of $15 to top up a $5 contribution made by the experimenters. In the second framing condition, decision makers were told that their $20 endowment had been taxed a $5 minimum contribution to the charity, and that they could choose the amount they would like to voluntarily add to this forced minimum transfer. Thus, the payoff structure was identical in both conditions, but the framing differed. While the second condition made the source of the funding for the forced transfer apparent to the decision makers (i.e., by framing the minimum contribution as a mandatory deduction from the decision maker’s endowment), the first condition left this source of funding implicit. Eckel et al. (2005) found that voluntary contributions to the charity were crowded out by the forced transfers only if it was made explicit that the minimum contributions were deducted from the decision makers’ endowment (i.e., in the second condition). No crowding out of voluntary contributions was observed if the source of its funding was not apparent to the decision makers (first condition). Hence, making the extrinsic incentive explicit in the form of a penalty to the participants’ endowment crowded out intrinsic motivations to contribute to the charity.

On a side note, identifying the circumstances under which extrinsic rewards may crowd out intrinsic motivations and thereby contribute to the reduction of the decision makers’ overall motivation (or task performance) could also have important implications for policy making. If incentives have the potential to reduce the desired behavior in question by undermining intrinsic motivation, this calls into question the use of cost-intensive incentive schemes (such as pay for performance) or other interventions aimed at boosting the desired behavior. For instance, Georgellis, Iossa, and Tabvuma (2011) argued that offering lower extrinsic rewards could actually increase the average quality of job matches in the public sector. Based on longitudinal data from the UK, these authors observed that individuals were attracted to the public sector by intrinsic motivation rather
than by the extrinsic rewards this sector offers. In a crowding out fashion, high extrinsic rewards could reduce the workers’ inclinations to accept public sector employment offers when they were highly intrinsically motivated to work in this sector. Making a similar argument, Rode, Gómez-Baggethun, and Krause (2015) argued that higher incentives could prove detrimental to fostering nature conservation behavior on the individual level. These authors reviewed the literature on different incentive schemes deployed to encourage environmental conservation behavior. There was evidence for motivation crowding out effects of financial incentives, challenging the effectiveness of widely-used economic interventions that make use of extrinsic rewards to promote environmental protection behavior. Given the urgency of sustainable protection of the environment in the present times, the detrimental impact of economic interventions on intrinsic motivation should be considered with caution before implementing large-scale conservation policies built on extrinsic incentives.

By contrast, in other settings the undermining effect of incentives seems less clear. For instance, Gerhart and Fang (2015) concluded that there was little evidence for an undermining effect of pay for performance on work motivation and creativity in the workplace. Hendijani and colleagues (2016) reported that monetary rewards increased academic performance regardless of whether an individual’s level of intrinsic motivation was high or low, calling the undermining effect of incentives in academic settings into doubt. Finally, Promberger and Marteau (2013) reviewed crowding out effects of incentives in the context of individual health. These authors argued that there was no evidence for the potential of incentives to undermine intrinsic motivation in health-related behaviors.

Taken together, extrinsic incentives may undermine performance when intrinsic motivation is high initially or when social considerations determine economic decisions. A recent meta-analysis supported the general validity of the motivation crowding out hypothesis. This analysis combined 183 studies and data of over 200,000 participants and confirmed that incentives were generally a good predictor of the quantity of performance. However, consistent with the crowding out effect, intrinsic motivation seemed less important for performance when performance-contingent incentives were offered (Cerasoli et al., 2014). By contrast, the evidence for the undermining effects of incentives is less clear for situations in which intrinsic motivation is low and when decisions do not
involve social or interpersonal conflict, as for instance in personal health-related behavior or in educational settings (see also Gneezy, Meier, & Rey-Biel, 2011; Promberger & Marteau, 2013). Consequently, in these situations, incentives are unlikely to interfere with intrinsic motivation and may successfully promote desirable behavior.

**Incentives and decision processes**

As mentioned above, if incentives are effective in terms of improving economic performance, this impact is usually assumed to emerge because incentives increase the effort individuals invest into a given task. However, the observation that incentives, in some situations, fail to increase task performance challenges the view of a strong incentive-effort-performance link. In addition, little is known about how exactly incentives may influence economic decision processes, as for instance, cognitive effort or information search. To promote our understanding of the effects of incentives on decision processes, researchers have only recently begun to use process tracing methods such as eye tracking (Uto, 2017), measuring pupil dilation (Alós-Ferrer, Jaudas, & Ritschel, 2019), or EEG (Achtziger, Alós-Ferrer, Hügelschäfer, & Steinhauser, 2015).

One line of studies that explored incentive effects on decision processes relied on a paradigm in which different decision strategies could be either in conflict (i.e., suggest different decisions) or in alignment (i.e., suggest the same response). In this Bayesian updating task (Achtziger & Alós-Ferrer, 2014; Charness & Levin, 2005), decision makers typically produce abundant errors, i.e., they make many suboptimal choices. Hence, this task is relatively difficult for decision makers and there is quite some room for performance improvements that could be induced by targeted interventions. This renders the Bayesian updating task particularly interesting for investigations of the incentive-effort-performance link, because the potential effects of incentives, or increased effort more generally, are not restricted by possible ceiling effects (e.g., if performance is hard to increase because it is already close to optimal even if no extrinsic reward is offered).

In a seminal study, Achtziger and Alós-Ferrer (2014) offered decision makers high versus low monetary rewards for optimal choices in the Bayesian updating task. Decision makers extracted a ball from one of two urns and were paid a low vs. high reward when
the ball was of a previously specified color, e.g., either black or white. The distribution of black and white balls in each urn was determined by one of two possible states of the world that occurred with commonly known probabilities. Thus, decision makers were aware of each state of the world’s base-rate probability, but the current state of the world remained unknown. After the first draw (with replacement), which facilitated inferences about the current state of the world, decision makers were asked to extract a second ball. The state of the world was constant across the two draws. Hence, a rational decision strategy facilitated optimized decisions in the second draw to maximize the payoff. This was possible by following Bayes rule, i.e., by integrating the new information gained from the first draw and the prior beliefs based on the known base-rate probabilities of the possible states of the world. In contrast, an associative decision strategy, based on reinforcement learning, suggested to stay with the same urn if the first draw had delivered a winning ball, and to shift if it did not (win-stay/lose-shift heuristic). This heuristic decision strategy produced suboptimal decisions in situations in which following Bayes’ rule would optimize payoff, that is, in conflict situations.

Achtziger and Alós-Ferrer (2014) found that higher incentives did not significantly improve performance in this task. That is, despite higher incentives offered for optimized decisions, error rates remained relatively high overall. Additionally, these authors reported that response times did not differ between high versus low incentive conditions. Longer response times would be expected if higher incentives led to increased cognitive effort. Hence, extrinsic rewards did not seem to influence effort (as indicated by response times) or performance (error rates) in the Bayesian updating task. This was rather puzzling, given the persuasion with which incentives are usually assumed to increase both effort and performance.

A follow-up study using the same paradigm provided further insights into the effects of incentives on decision processes. Achtziger et al. (2015) replicated the failure of incentives to increase performance in the Bayesian updating task. Using EEG to track the neural correlates of reward processing, they found evidence for the role of incentives in increasing the reliance on reinforcement learning, which was prone to producing errors in this task by means of the win-stay/lose-shift heuristic. When immediate feedback on decision outcomes was provided, incentives led to the win/lose feedback becoming more prominent (as indicated by differences in the feedback-related negativity, an early event-
related potential triggered by the feedback), consequently increasing the reliance on the faulty reinforcement heuristic and resulting errors.

But at the same time, there was no decrease of overall performance. Also, remember that high versus low incentives did not affect response times in the study by Achtziger and Alós-Ferrer (2014). If higher incentives increased the reliance on the reinforcement heuristic, one would expect responses in the high incentive condition to be faster on average (because the heuristic can be expected to produce faster responses on average), and performance to be decreased on average (because the heuristic should produce more erroneous responses on average). However, this was not the case, response times and error rates were not different between the high and low incentive conditions.

One explanation for this finding could be that higher incentives elicited counteracting effects on decision processes. On the one hand, incentives led to increased reliance on the reinforcement heuristic, facilitating fast decisions and increasing error rates. On the other hand, incentives may also have increased the cognitive effort invested in the task, and thereby positively affected conflict detection and the inhibition of heuristic erroneous responses. Viewed in isolation, this effect of incentives on effort should produce slower decisions and improve performance. However, the combined effects of incentives on reinforcement and effort, then, would cancel each other out on average, resulting in the observed pattern, i.e., no difference in response times and error rates between high versus low incentive conditions. Evidence from a recent pupil dilation study supported this view (Alós-Ferrer et al., 2019). It appeared that higher incentives indeed increased the cognitive effort invested in the task, as indicated by greater changes in pupil dilation, while overall task performance remained unaffected by the variation of incentives.

**Conclusion**

Incentives do seem to be vital for economic performance, but the relation of incentives, effort, and performance is far from straightforward and the way they interact with each other may be qualitatively distinct across different economic decision tasks. While the traditional convention in economics holds that financial incentives are
instrumental for improving economic performance, recent insights emphasize that, under certain conditions, incentives may actually impair performance (e.g., Frey & Jegen, 2001; Gneezy & Rustichini, 2000b), or produce counteracting effects on effort and reliance on heuristics that cancel each other out, so that performance appears to be unaffected by incentives (Achtziger & Alós-Ferrer, 2014; Achtziger et al., 2015). It is thus crucially important to consider the specifics of distinct decision environments when discussing the effectiveness of financial incentives for modifying behavior. Several characteristics of the decision environment, such as complexity, difficulty, feedback, or time-pressure may considerably affect the impact of financial incentives on economic performance (Camerer & Hogarth, 1999; Hogarth et al., 1991). By contrast, overall performance in economic decision tasks may remain unaffected by financial incentives, even if the latter have a strong impact on decision processes (Alós-Ferrer et al., 2019; Uto, 2017).

Two main conclusions can be drawn from this chapter. First, it can be safely asserted that financial incentives are important determinants of economic decisions and their underlying processes. However, as Gneezy et al. (2011, p. 206) put it: “incentives do matter, but in various and sometimes unexpected ways”. While research on motivation crowding out theory provides a solid foundation for understanding the circumstances under which financial incentives may undermine intrinsic motivation, we still do not fully understand the interplay between incentives and other sources of motivation. In other words, the relation of financial incentives and distinct motivational processes beyond the individual’s level of intrinsic motivation for a given task remains largely unknown. This is analogously true for the possible interaction of incentives with processes of volition, i.e., the willful regulation of goal-directed behavior.

Second, there is a lack of research into the effects of financial incentives on the processes underlying economic decisions. A closer look at decision processes, rather than just assessing incentive effects on performance, promises to reveal important insights into the cognitive mechanisms underlying the behavioral effects of incentives, or the failure of incentives to produce the desired behavioral effects. Only recently have scholars begun to consider incentive effects on the level of decision processes. This approach afforded interesting insights and outlined promising avenues for further empirical inquiry.
CHAPTER 4

OVERVIEW OF THE EMPIRICAL WORK

This chapter maps out a research program to investigate the effects of motivation, volition, and financial incentives on economic decisions and their underlying processes. In preparation of such investigation, I first narrow down the main research question of the present dissertation, based on the theoretical considerations in the previous chapters. I then explicate the specific hypotheses about motivation, volition, and incentive effects on economic decisions and their processes, which shall be tested in several experimental studies. Finally, preparing the Empirical Part of this dissertation, I briefly sketch the four experiments designed to submit these hypotheses to empirical scrutiny.

Research question

The main objective of the present dissertation is an investigation of the joint effects of motivation, volition, and financial incentives on economic decisions and their processes. As mentioned earlier (see Chapter 1: Motivation and Volition in Economic Decisions), prior work has already examined the roles of goals, implementation intentions, and regulatory foci in making economic decisions, yielding some important insights into the relevance of motivation and volition for economic decision making. However, this previous work has mainly investigated motivation and volition by measuring intrinsic motivation via self-reports, studying the impact of different kinds of goals on economic performance, or by examining how furnishing these goals with implementation intentions may foster economic decisions. Only few studies so far have addressed how economic decisions and their processes may be influenced by an experimental variation of motivational and volitional processes. Studying motivation and volition through an experimental manipulation that systematically varies the cognitive
procedures activated during the pre-decisional and the pre-actional action phases promises to deliver important insights into how motivational and volitional processes shape economic decisions and their processes. Furthermore, a systematic experimental manipulation offers more control over potentially confounding factors than just surveying motivation by means of self-reports.

Thus, as I have argued above, there is a need for more research assessing motivation and volition effects beyond the measurement of intrinsic motivation and assessing the impact of goals on performance. In particular, little is known about the influences of motivation and volition on economic decision processes of, for instance, cognitive effort, information search, or affective arousal. It is the central aim of the present dissertation to address this gap in the decision research literature. The main research question can thus be summarized as follows: How do experimentally induced motivational and volitional states influence economic decision processes, and what is the role of financial incentives in modulating their impact?

I concentrate on the experimental manipulation of motivational and volitional states of mind, as defined in the mindset theory of action phases (see Chapter 2: Mindset Theory of Action Phases), to study the distinct influences of motivation and volition on economic decisions and their processes. To that end, I use a well-established procedural priming manipulation which reliably activates the cognitive procedures that are unique to motivational and volitional states of mind (i.e., the deliberative and implemental mindsets). In three experiments, I examine the carry-over effects of these distinct cognitive orientations on choices and decision processes in subsequent economic decision tasks. Doing so facilitates a characterization of the distinct effects of motivational and volitional processes on economic decisions and their processes beyond just measuring motivation via self-reports or evaluating how different goals may affect performance, as done in many prior studies. Furthermore, this approach facilitates the investigation of the distinct influences of motivation and volition on economic decisions based on a unified theoretical framework that combines these different processes within one model of goal-directed action. Thus, it bears the potential to pave the way for an integration of motivation and volition into a formal choice model.
As mentioned above (see Chapter 3: Incentives), extrinsic incentives, particularly in the form of monetary rewards, have been found to be important determinants of motivational processes in economic decisions. However, the impact of incentives on economic decision processes is far from straightforward. It appears that there are numerous restrictions regarding the effectiveness of financial incentives for improving economic performance. Since it is important to incentivize behavior in choice experiments to mirror the conditions of real-life decision making in the laboratory as closely as possible, I use performance-based financial incentives in all studies reported in this dissertation. The impact of incentives could potentially also rely on other motivational and volitional processes. To explore the possibility of interactions between motivation, volition, and financial incentives, I include a variation of financial incentives in two experiments (Chapter 5: The Interactive Effects of Mindsets and Incentives). This allows for a test of the hypothesis that higher incentives will improve performance in an economic decision task through their impact on the effort invested in the task.

To address the main research question, a more fine-grained approach to measuring the involved cognitive processes is required. Using eye tracking, I examine how the deliberative and implemental mindsets influence decision processes of cognitive effort (indicated by decision times), information search (visual attention), and affective arousal (pupil dilation) in an incentivized lottery choice task (Chapter 6: Mindset Effects on Decision Processes Under Risk). Presumably, these decision processes are determined by the current motivational or volitional state of mind, and therefore, choices in this decision task might also be affected.

A further objective of the present dissertation concerns the affect-motivation link in economic decisions. The decision research literature describes several suboptimal choice regularities (i.e., observed violations of expected utility theory, the standard choice model in economics) which may rely on distinct motivational and affective processes triggered by the specific task at hand. For instance, decision makers are typically assumed to be attracted by sure gains when choosing between (more or less) risky lotteries (e.g., Kahneman & Tversky, 1979). From a motivation researcher’s perspective, this presumed attraction to certainty expresses a pronounced approach tendency elicited by the prospect of the sure gain, and it might be accompanied by a (more or less) arousing affective experience. By contrast, information search prior to making economic decisions has also
been described as biased toward the anticipated hedonic quality of the information (e.g., Karlsson, Loewenstein, & Seppi, 2009). In other words, decision makers may eschew certain information if they expect it will cause them psychological discomfort. Selective attention to certain decision attributes in this way would express a motivational tendency of avoidance, which, again, might be the concomitant of a specific affective experience in response to negatively valenced information. As a secondary objective, the present dissertation seeks to shed some light on these presumed relations among motivation, affect, attention, and choice in decisions under risk (see Chapter 7: The Zero Effect in Risky Choices).

Hypotheses

This section explicates the specific hypotheses to be tested in the four experiments reported in the Empirical Part of this dissertation. I begin with the consideration of incentive effects on economic performance and decision processes, before summarizing the predictions about mindset effects on choices and processes in economic decisions. Next, I map out the possible interactive effects of incentives and mindsets. The hypotheses about incentives, mindsets, and their interaction, to be tested in Experiments 1a, 1b, and 2 are summarized in Table 1. Finally, reaching beyond the study of the deliberative and implemental mindsets, I describe some considerations regarding the impact of motivation and affective processes on decisions under risk, as Experiment 3 focuses on the motivation-affect link in risky choices.

Incentives

As mentioned earlier, financial incentives are often assumed to increase the effort invested in a task and thereby improve performance (e.g., Duckworth et al., 2011; Hertwig & Ortmann, 2001). However, in some situations, the proposed relation among incentives, effort, and performance does not hold. Incentives may sometimes have no effect on performance (e.g., Achtziger & Alós-Ferrer, 2014) and may, under certain conditions, even be detrimental to performance (Fehr & Falk, 2002; Frey & Jegen, 2001).
Specifically, financial incentives may in some situations crowd out the decision makers’ intrinsic motivation to perform well in a given task, and thereby impair performance (Cerasoli et al., 2014). Hence, the effects of financial incentives may greatly depend on other sources of motivation and differ dramatically across different decision tasks.

Based on the considerations in the previous chapters, several predictions can be made regarding the effects of financial incentives on economic decisions and their processes. First, economic research tradition underscores the importance of incentivizing behavior in choice experiments, because, relative to a fixed rate compensation regardless of actual performance, performance-based financial incentives are assumed to yield improved task performance. This is also consistent with the notion that incentives are most effective in terms of their influence on effort and performance when they are salient, i.e., when directly linked to individual performance (Cerasoli et al., 2014). Therefore, it can be expected that decision makers who are offered performance-based incentives perform better in an economic decision task than decision makers who just receive a fixed rate payment for the same task. That is, when decisions are incentivized, it can be expected that participants make fewer errors. This performance improvement is assumed to rely on increased effort, because providing additional monetary rewards for correct responses presumably stimulates the effort participants will invest in the decision task. To the extent that response times can be considered as a measure of cognitive effort, it can be expected that decision makers make slower choices when offered performance-based incentives.

H1 Performance-based financial incentives improve performance in an economic decision task, compared with a fixed rate payment.

H2 Performance-based financial incentives increase response times in an economic decision task, compared with a fixed rate payment.

In addition, when varying the absolute amount of the financial incentive, it can be expected that higher incentives, compared with lower incentives, increase the effort invested in a task and thus improve performance. This should result in slower decisions (i.e., increased response times) and improved overall performance in an economic decision task. Hence, decision makers who are offered a high incentive should outperform
decision makers who are offered only a low incentive for the same economic decision task.

H3  High financial incentives improve performance in an economic decision task, compared with low incentives.

H4  High financial incentives increase response times in an economic decision task, compared with low incentives.

Note, however, that recent evidence pointed to the possibility of antagonistic effects of financial incentives on decision processes. In particular, in some economic decision tasks, higher incentives appeared to produce counteracting effects on decision processes, such that they increased the reliance on fast (but faulty) heuristics but also increased the effort invested in the task (Achtziger et al., 2015; Alós-Ferrer et al., 2019). These effects may cancel each other out on average, giving rise to the false impression that providing higher incentives does not influence economic decisions. If higher incentives, relative to lower incentives, indeed increase both the reliance on heuristics as well as the effort invested in the task, the latter two predictions cannot be expected to hold. In this case, it would in fact be expected that lower versus higher incentives do not affect performance or response times. Hence, the notion of counteracting effects of incentives on decision processes provides an explanation of earlier findings that were inconsistent with H3 and H4, i.e., the observations that higher incentives did not affect performance or response times in economic decision tasks (e.g., Achtziger & Alós-Ferrer, 2014; Camerer & Hogarth, 1999).
Table 1
*Summary of the hypotheses about incentives, mindsets, and their interaction to be tested in Experiments 1a, 1b, and 2.*

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<th>Predictions</th>
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<td>H3</td>
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<td><strong>Deliberative mindset</strong></td>
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<td><strong>Implemental mindset</strong></td>
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The deliberative and implemental mindsets

Several hypotheses about the impact of the deliberative and implemental mindsets on decision outcomes and processes may be derived from their differential cognitive characteristics. The mindset hypotheses to be tested in the present dissertation rest on two main aspects which distinguish between the mindsets: the difference in receptivity to information, or general open-mindedness, and the distinct processing of information related to desirability and feasibility, or cognitive tuning (Achtziger & Gollwitzer, 2018; Gollwitzer, 1990, 2012; Gollwitzer & Bayer, 1999).

Regarding the distinctive information processing (cognitive tuning), Gollwitzer (1990) argued that information related to the desirability of a personal concern is assessed in an impartial manner in the deliberative mindset, but that assessment is partial to the chosen action in the implemental mindset. This difference in handling desirability-related information seems functional, given that the deliberative mindset is concerned with goal setting and the implemental mindset should facilitate goal striving. When deliberating the positive and negative consequences of various alternative courses of action to evaluate their comparative desirability, it is preferable to yield assessments that are objective and unbiased. However, when an action has been selected for implementation, it seems more important to boost commitment and persistence to facilitate action initiation. Doubts about a project’s desirability might hinder this process and should thus be counteracted. The implemental mindset achieves this by biased inferences about the chosen action’s desirability and a partial assessment of that action, boosting its desirability.

Similarly, the subjective evaluation of an outcome’s attainability should be accurate in the deliberative mindset to facilitate the comparison with alternative courses of action. Yet, (illusory) optimistic analyses of an action’s feasibility would support goal striving during the pre-actional phase. Hence, the processing of information related to the desirability of an action can be expected to be impartial in the deliberative mindset but partial to the chosen action in the implemental mindset. Processing information related to the feasibility of an action can be expected to be accurate in the deliberative mindset but biased and optimistic in the implemental mindset (see also Beckmann & Gollwitzer, 1987; Gollwitzer & Bayer, 1999; Gollwitzer & Kinney, 1989; E. Harmon-Jones & Harmon-Jones, 2002; H. Heckhausen & Gollwitzer, 1987).
On the receptivity to information (open-mindedness), Gollwitzer (1990) explained that a general open-mindedness toward processing all kinds of incoming information would be beneficial in the deliberative mindset, because the relevance of specific pieces of information to assessing a goal’s desirability and feasibility becomes clear only after they have been considered. For the implemental mindset, however, such a general open-mindedness to information could prove detrimental to action initiation. To facilitate goal implementation, attention is focused in the implemental mindset to specific information in order to identify favorable conditions for action initiation. In that sense, the implemental mindset is associated with a certain closed-mindedness and cognitive tuning toward information that support goal achievement (see also Beckmann & Gollwitzer, 1987; Fujita et al., 2007; Gollwitzer & Bayer, 1999; Gollwitzer & Kinney, 1989; H. Heckhausen & Gollwitzer, 1987).

**Deliberative mindset.** As noted, the deliberative mindset activates cognitive procedures that are conducive to the motivational task of goal setting. It is characterized by a broad attentional focus, open-mindedness (i.e., heightened receptivity) to information of all kinds, and a rather realistic, impartial assessment of these information in terms of their relevance for a goal’s desirability and feasibility. These characteristics of the deliberative mindset support goal setting, since they facilitate a well-balanced weighing of competing goals’ positive and negative consequences and a realistic assessment of these goals’ attainability. Moreover, the deliberative mindset cognitively tunes an individual toward information related to a goal’s desirability and feasibility, further supporting the process of setting goals.

Once activated, these cognitive procedures remain active for some time and carry over to subsequent tasks. When carried over to economic decision tasks, the cognitive procedures instigated by the deliberative mindset can be expected to affect economic decisions and their underlying processes. The benefits of the deliberative mindset for improved performance have been demonstrated in various fields (e.g., Griffith et al., 2015). In particular, decision makers may benefit from a deliberative mindset in tasks that require the careful weighing of all the available evidence in favor and against several choice options, or when the accurate (i.e., realistic and impartial) evaluation of potentially misleading information is vital to improve decisions. In fact, many economic decision
tasks can be seen in line with these task demands. Often, careful deliberation and accurate evaluation of incoming information can improve economic performance.

In the deliberative mindset, impartiality of information processing, heightened receptivity to information, and a general open-mindedness to information of all kinds are likely to result in more comprehensive information search prior to making choices in economic decision tasks. This should result in more information being acquired, and thus, a prolonged period of pre-decisional information search. Therefore, relative to the implemental mindset and the control condition, longer decision times can be expected in the deliberative mindset. While the extensive search for information may be rather time-consuming, the increased effort to consider and impartially assess all available information may actually prove beneficial for economic performance in many economic decision tasks. Supposedly, the comprehensive consideration and impartial processing of all available information should support finding the correct response to economic decision problems, and thus, reduce error rates in economic decision tasks. Therefore, improved performance can be expected for decision makers in a deliberative mindset, relative to implemental mindset and control condition.

H5 The deliberative mindset, relative to a control condition, improves performance in an economic decision task.

H6 The deliberative mindset, relative to a control condition, increases response times in an economic decision task.

H7 The deliberative mindset, relative to a control condition, increases information search in an economic decision task.

**Implemental mindset.** The implemental mindset supports the volitional task of goal striving by the activation of cognitive procedures that are conducive to the successful implementation of goal intentions. A narrow attentional focus, closed-mindedness in terms of receptivity to incoming information, and a general tendency to process information in an illusorily optimistic manner characterize this cognitive orientation. Also, the implemental mindset cognitively tunes individuals toward information related to the implementation (feasibility) of a goal, resulting in preferential processing of such information. These features of the implemental mindset facilitate the successful
translation of goal intentions into action by optimistically biasing success expectancies, raising persistence in goal striving, and shielding the current goal from temptations or deliberative re-considerations.

Like the deliberative mindset, the implemental mindset remains activated for some time even after planning steps of action is completed. When individuals subsequently engage in an unrelated task, the implemental mindset is still in place and influences decisions and their processes in that task. For economic decision tasks, the cognitive procedures activated alongside the implemental mindset may prove beneficial for performance if fast decision making based on salient information is required. However, when careful evaluation of all available information is necessary to optimize decisions (as is in many economic decision tasks), the implemental mindset’s propensity to facilitate fast and closed-minded information processing may impair economic performance.

In the implemental mindset, partial information processing, reduced receptivity to information, and a general closed-mindedness should result in reduced pre-decisional information search. These processes may also increase an individuals’ susceptibility to decision biases and thereby negatively affect performance. Furthermore, cognitive tuning toward implementation-related information may lead to preferential processing of information related to the feasibility of a goal. If this information is considered preferentially, it may also receive a greater weight in decision making, further biasing the decision processes.

Therefore, the implemental mindset should be associated with more impulsivity, increased susceptibility to decision biases, and speeded choices. When the decision task’s performance goal (i.e., choose the correct response) is supported by an implemental mindset, decision makers should be prone to overestimate the attainability of this goal and be more likely to make a rushed step in decision making, particularly when considering the erroneous response option. Based on the way that (economic) decision problems are usually crafted, the faulty response option often seems correct at first glance but proves incorrect only after careful deliberation, thus invoking intuitive or heuristic errors. Since decision makers in an implemental mindset should not typically engage in careful deliberation, higher error rates and shorter decision times can be expected, relative
to the deliberative mindset and the control group. Furthermore, cognitive tuning toward feasibility-related information should translate into an attentional bias toward these information, which in turn should affect behavioral choices in economic decision tasks. Hence, I predicted the following effects of the implemental mindset on economic decisions and their processes:

- **H8** The implemental mindset, relative to a control condition, impairs performance in an economic decision task.
- **H9** The implemental mindset, relative to a control condition, decreases response times in an economic decision task.
- **H10** The implemental mindset, relative to a control condition, increases the processing of feasibility-related information in an economic decision task.

**Interaction of mindsets and incentives**

To the extent that performance-based financial incentives provide an additional extrinsic source of incentive value (i.e., desirability) for the goal to perform well in economic decision tasks, one might suppose there could be an interaction of mindsets and financial incentives. The implemental mindset activates cognitive procedures that lead to the systematic overestimation of an outcome’s attainability, and biased inferences about its desirability. Decision makers in an implemental mindset should thus overestimate the attainability with which an aspired outcome can be achieved. As described above, this could lead to relatively more impulsivity, rushed steps in decision making, and a generally higher susceptibility to decision biases for implemental participants.

Earlier research has shown that financial incentives may produce antagonistic effects on decision processes in a way that they, on the one hand, increase the reliance on fast but faulty heuristics (Achtziger et al., 2015), and on the other hand, also stimulate the effort participants invest into a task (e.g., Alós-Ferrer et al., 2019). These effects might cancel each other out on average. Yet, it is an interesting parallel that both the implemental mindset and financial incentives could increase the decision makers’
reliance on heuristic processes, or in other words, their susceptibility to decision biases generated by automatic decision processes. Presumably, these effects could be multiplicative in nature when combined, rather than additive, since increased reliance on automatic processes from one source (e.g., the incentive) may reinforce the reliance on automatic processes that comes from another source (e.g., the implemental mindset). That is, decision makers in an implemental mindset may be more prone to rely on decision heuristics when their choices are incentivized, and perhaps even more so than an additive effect of incentives and being in an implemental state of mind would suggest. In statistical terms, this multiplicative effect of the implemental mindset and financial incentives in (detrimentally) affecting economic performance would be expressed by an interaction.

Another way the potential interaction of mindsets and incentives could influence economic decisions is founded on the capacity of the deliberative mindset to carefully and impartially consider desirability-related information. As mentioned, offering additional monetary rewards for correct choices in an economic decision task increases the desirability of correct responses in that task. While many economic decision tasks may not be intrinsically desirable to the decision maker if no directly salient incentive is provided, adding the prospect of monetary rewards contingent on task performance certainly renders that task more attractive, i.e., more desirable. Remember that, in general, the deliberative mindset is associated with rather accurate representations of a task’s desirability. Conceivably, the potential benefits of being in a deliberative mindset (i.e., comprehensive pre-decisional information search, impartiality of information processing) could rely on the initial assessment of the task’s desirability and only become relevant if the task desirability is sufficiently high. That is, decision makers may benefit from a deliberative mindset only when choices are incentivized, because their (accurate) evaluation of a given decision task’s desirability simply does not warrant the increased effort of carefully searching for and weighing the available evidence if no (or too little) incentive is provided for improved performance. If this were the case, the deliberative mindset should interact with financial incentives such that performance improvements, slower decisions, and increased effort in information search become apparent only when choices are properly incentivized.

This could also explain why earlier research failed to detect deliberative mindset effects on task performance and decision processes, as outlined above (Rahn et al.,
Rahn et al. (2016b) observed no increase in decision times and information search (indicated by visual attention) in a lottery choice task when decision makers were in a deliberative mindset. However, choices were not incentivized in this study. It is one possibility that the beneficial effects of the deliberative mindset did not unfold simply because the task was not sufficiently desirable due to a lack of appropriate incentivization.

These described interactions among the deliberative and implemental mindsets, and financial incentives, are only two possibilities how mindsets may interact with monetary rewards or other sources of motivation. Certainly, these conjectures do not claim to have exhaustively explored to possibility of interactive effects of mindsets and incentives. Since several other directions are conceivable in which mindsets could interact with financial incentives, I refrain from posing specific predictions about their interaction beyond the propositions outlined above. Instead, in this case, it seemed natural to let the data speak to the proposed interactive effects of mindsets and incentives. The respective analyses reported in the Empirical Part should therefore be considered as largely explorative.

**Concluding remarks**

It is a secondary objective of the present dissertation to investigate the affect-motivation link in economic decisions. It is an established finding in decision research that decision makers faced with risky lottery choices opt for sure gains whenever available (e.g., Kahneman & Tversky, 1979). However, a recent working paper by Incekara-Hafalir and Stecher (2016) challenged the view that decision makers are attracted to certainty and proposed that, instead, decision makers generally seek to avoid receiving decision outcomes that entail no gain at all. Both the attraction to certainty and the avoidance of zero-outcomes can be expected to trigger unique motivational processes and, presumably, distinct affective experiences. Experiment 3 examined these competing predictions about decisions in the lottery choice paradigm and the different motivational and affective processes elicited by specific gamble attributes like sure gains and zero-outcomes.

Since Experiment 3 was inspired by an unexpected observation made in Experiment 2, the specific hypotheses to be tested in this experiment are stated in the
respective chapter below (see Chapter 7: The Zero Effect in Risky Choices). In a nutshell, it was expected that zero-outcomes in a lottery choice task (i.e., decision outcomes with the value zero) would trigger motivated avoidance of these outcomes that should translate into attentional and choice biases. That is, it was expected that zero-outcomes would be disregarded in terms of visual attention and that gambles which include such outcomes would be chosen much less frequently. In addition, arousal should be significantly increased when zero-outcomes were included in a lottery. Since these preliminary predictions were derived based on the findings from Experiment 2, and because Experiment 3 should be considered as an explorative experimental study to follow up on the surprising observations made in the previous study, it seemed natural to explicate the hypotheses only after the groundwork had been laid in Experiment 2.

It should be noted that some studies exist which already used the deliberative and implemental mindsets to study motivation and volition in economic decisions. These earlier studies include investigations of mindset effects on confidence judgments, decision heuristics (Hügelschäfer & Achtziger, 2014), and risk taking (Keller & Gollwitzer, 2017; Rahn et al., 2016a, 2016b); mindset effects in the Bayesian updating paradigm described above (Li et al., 2019); mindset effects on attentional decision processes (Büttner et al., 2014, Study 3); and mindset effects on predictions of time (V. Brandstätter et al., 2015).

These studies generated interesting insights into the relations of the deliberative and implemental mindsets and economic decisions. For instance, Keller and Gollwitzer (2017) and Rahn et al. (2016a) observed that decision makers in an implemental mindset took higher risks than deliberative decision makers. Li et al. (2019) reported that the implemental mindset supported optimized decisions in the Bayesian updating task. Büttner and colleagues (2014, Study 3) found that implemental participants focused attention more on foreground objects, rather than peripheral or background information, when viewing urban and nature scenes. A more comprehensive review of the prior findings on how mindsets relate to economic decisions and attentional processes is presented above (see Chapter 2: Mindset Theory of Action Phases).

While these studies were certainly related to the main research question of the present dissertation, they were also critically different from it. The present work’s main
objective is the investigation of the joint effects of mindsets and financial incentives on economic decisions, and their influence on decision processes such as cognitive effort, pre-decisional information search, and affective arousal. That is, the present work combines three aspects of economic decision making: the investigation of mindset effects in incentivized decision environments, a closer look at potential interactive effects of mindsets and incentives on choices, and the examination of mindset effects on decision processes. While prior work has already addressed these three aspects on isolation, there is no study thus far which combined them within one experiment.

To reiterate, there is earlier work on mindsets in judgment and decision making when choices were not incentivized (Hügelschäfer & Achtziger, 2014; Rahn et al., 2016b) and prior work on mindsets and economic decisions in which individual earnings were directly linked to performance in the task (Keller & Gollwitzer, 2017; Rahn et al., 2016a). But no study to date investigated the potential interactive effects of mindsets and incentives by including systematic variations of both mindsets and incentives within one experiment. As mentioned, there is earlier work on the effects of mindsets on economic decisions in incentivized tasks (Keller & Gollwitzer, 2017; Rahn et al., 2016a), but these studies examined only choices, not decision processes. Analogous, there is prior work on the effects of mindsets on decision processes, for instance, cognitive effort and pre-decisional information search (Büttner et al., 2014; Rahn et al., 2016b). Yet, in these studies, choices were not incentivized, i.e., they had no real consequences in terms of individual earnings. So far, there seems to be no study that examined the effects of the deliberative and implemental mindsets on attentional decision processes when individual earnings were contingent on performance in the task.

The present dissertation addresses these two issues and (a) tests for potential interactive effects of mindsets and incentives in economic decisions, and (b) examines mindset effects on decision processes in incentivized economic decision tasks. To address the first issue, I designed two experiments in which both mindsets and incentives were systematically varied (Experiments 1a, 1b). A third experiment addressed the second gap, the lack of research on mindset effects on decision processes under incentivization (Experiment 2). Finally, a follow-up study (Experiment 3) explored the affect-motivation link in relation to specific attributes of the decision environment that may be considered as particularly prone to instigate affective and motivational processes in risky choices.
CHAPTER 5

THE INTERACTIVE EFFECTS OF MINDSETS AND INCENTIVES

The line of studies reported in this chapter served three main objectives. First, the studies were designed to test the above formulated hypotheses about the effects of financial incentives on economic performance. The second objective was an exploration of mindset effects on economic decisions. Some earlier research had provided initial evidence for the idea that the deliberative and implemental mindsets may relate to performance in economic decision tasks (e.g., Hügelschäfer & Achtziger, 2014; Keller & Gollwitzer, 2017; Li et al., 2019). The studies reported hereafter scrutinized such potential mindset effects on economic decisions, using a different kind of economic decision task than earlier research. Third, the studies explored the possibility of interactive effects between the deliberative and implemental mindsets, and different forms of financial incentives, on performance in economic decisions.

Two online experiments with large sample sizes (Experiments 1a, 1b) were conducted to address these aims. In both studies, the experimental design was very similar. The crucial difference between Experiment 1a and Experiment 1b was the manipulation of the incentive: In Experiment 1a, decision makers either received a performance-based financial incentive or were paid a fixed rate bonus. That is, participants were paid based on the number of correct responses (performance condition) or they received a bonus regardless of their performance in the decision task (fixed payment condition). In both conditions, there was a fixed base payment that ensured minimum earnings consistent with the current US minimum wage. The fixed rate bonus or performance-based bonus were added to this base payment. Taking a closer look at incentive contingency on task performance, Experiment 1b provided performance-based financial incentives in two conditions, but the magnitude of the monetary reward was varied. Participants received either a high or a low bonus payment for each correct
response in the decision task. Again, this high or low bonus payment was added to a fixed base payment that ensured minimum earnings consistent with minimum wage.

These two experiments were designed to address (a) the hypotheses H1 through H4 about incentive effects on economic decisions, (b) the hypotheses H5, H6, H8, and H9 about mindset effects on economic decisions, and (c) to explore the potential interactions of the deliberative and implemental mindsets with financial incentives (H11), as outlined in the previous chapter. In short, Experiment 1a facilitated a test of the hypothesis that performance-based incentives, relative to fixed rate payments, would increase the effort invested in a task, and thus, improve performance. Experiment 1b tested whether increasing the absolute amount of the performance-based financial incentive would lead to improved performance, as suggested by the presumed linear relation of incentives, effort, and performance. In both experiments, the hypotheses that being in a deliberative mindset may improve economic decisions, while being in an implemental mindset may reduce economic performance, were tested. As mentioned, a third objective was the exploration of possible interactions of mindsets and financial incentives. For a more elaborate description of the hypotheses to be tested in Experiments 1a and 1b, see Chapter 4: Overview of the Empirical Work.

Experiment 1a

Method

Participants and design. The study followed a 3 (between, mindset: control vs. deliberative vs. implemental) × 2 (between, incentive: fixed rate vs. performance-based) experimental design. Crossing the two factors mindset and incentive resulted in six experimental conditions. Performance measures (correct responses, decision times) of a decision task consisting of 15 moderately difficult items served as the main dependent variables. During the decision task, the number of clicks outside the current browser tab was counted to provide a proxy for cheating behavior. The measure reflected cheating to the extent that clicks outside the browser tab were used to search online for the correct response to the current decision problem in process.
A target sample size of $N = 300$ participants was determined prior to data collection to ensure $n = 50$ participants in each cell of the design. To account for foreseeable exclusions, three hundred and forty participants were recruited from an online participant pool (Prolific, www.prolific.co, Oxford, UK) to take part in the online study. The anticipated average duration of the study was 20 to 25 minutes. Participants were randomly assigned to one of the six experimental conditions and received a base payment of £2.30 (approx. €2.60). The base payment was determined to approximate US minimum wage (currently $7.25 per hour, approx. €6.40). In addition to this base payment, participants received either a fixed bonus (£0.80) or a performance-based bonus payment. The performance-based payment was set at £0.10 per correct response in the decision task to ensure comparable average earnings of the in both conditions. Since the decision problems used in this study were of medium difficulty (see Procedure and materials subsection), it was expected that participants, on average, would provide correct responses to seven or eight out of the 15 problems used in this study. Hence, an average bonus payment of £0.80 was anticipated in the performance-based incentive condition.

Due to technical issues (e.g., missing data) or inferior data quality (e.g., participants did not work on the task properly as instructed), 47 participants were screened out and excluded prior to the analysis. Hence, the final sample size on which all analyses were based, was $N = 293$ (129 males; $M_{age} = 32.65$ years, $SD = 12.00$), roughly equally distributed across the mindset conditions: $n_{con} = 107$, $n_{del} = 92$, and $n_{imp} = 94$; and the two incentive conditions: $n_{fixed} = 150$ and $n_{performance} = 143$.

**Procedure and materials.** A browser-based web application for online data collection was used to implement the experiment (SoSciSurvey, www.soscisurvey.de, Munich, Germany). All participants provided informed consent on the first page prior to starting the study. Participants were informed that the study was comprised of two (seemingly unrelated) parts. First, participants worked on a task inducing either a deliberative mindset, an implemental mindset, or a neutral (control) mindset. Once activated, the cognitive procedures associated with the deliberative and implemental mindsets should remain stable for some time and affect information processing in subsequent tasks, regardless of whether their content was linked to the mindset task (see, for instance, Gollwitzer, Heckhausen, & Steller, 1990; Rahn et al., 2016a). In the second part, participants worked on 15 moderately difficult decision problems which were
adapted from the cognitive reflection test (Frederick, 2005; Toplak, West, & Stanovich, 2014) and the probability judgment literature (e.g., Fisk, 2017; Pennycook & Thompson, 2017).

**Experimental manipulation: Mindsets.** The traditional mindset induction task by Gollwitzer and Kinney (1989; see also Hügelschäfer & Achtziger, 2014) was adapted for the online data collection in the present study. The task was developed to induce either a deliberative mindset by asking participants to carefully consider the pros and cons of a self-chosen personal problem, or to induce an implemental mindset by having participants think about the implementational steps of action required to realize a self-chosen personal project.

Participants in the deliberative mindset condition were asked to think about an unresolved personal problem of their own choosing. They were instructed to pick a topic of personal relevance, which they had been pondering for some time and found difficult to resolve, and for which a decision had not yet already been made in terms of choosing a specific course of action to pursue. As a second step, participants were asked to indicate the potential positive and negative consequences associated with acting on their personal problem versus leaving things as they were, and to rate the probability of occurrence of each of these consequences. An example (“Should I go on a 10-day camping trip with my friends in the summer or not?”) was provided to further familiarize the participants with the task before they started to deliberate about their own personal problem.

In the implemental mindset condition, participants were asked to name a relatively complex personal project that had been on their minds for some time and was currently important to them, and which would not be easy to implement. They were instructed to pick a personal project which they intended to realize or accomplish but had not yet acted upon. Subsequently, participants were asked to list up to five steps of action necessary to realize their project, and to indicate for each action step when, where, and how they intended to act. Before the participants started to plan their personal projects, an example (“I intend to go on a 10-day camping trip with my friends in the summer.”) was provided to familiarize them with the task.

In the control (neutral mindset) condition, participants worked on a thought listing task which prompted them to write down up to 20 thoughts that came to their minds,
regardless of content or relevance (see also E. Harmon-Jones & Harmon-Jones, 2002; Li et al., 2019, using a similar procedure in the neutral mindset condition). They were asked to let their thoughts run freely and to report them accurately. An example list of thoughts (e.g., “I should call my mom later today.”) was provided before the participants started listing their own thoughts. This task was used for the control condition mainly to compensate for the time it took participants in the other conditions to complete the respective mindset tasks. To hold the anticipated duration of the study, and thus the compensation, balanced across all experimental conditions, it was important to implement a task in the control condition that would keep the participants busy for an approximately equal amount of time, so that the appropriate compensation, in relation to the time required to process the study, was ensured in all conditions.

Note that in previous research (E. Harmon-Jones & Harmon-Jones, 2002; Keller & Gollwitzer, 2017; Li et al., 2019), a neutral mindset condition was included to account for the potentially confounding effect of workload fatigue induced by the mindset task. However, a recent study showed that a baseline condition in which no additional task was administered prior to the experimental task did not differ from the neutral mindset condition in terms of economic performance (i.e., error rates and response times in a Bayesian updating task; see Li et al., 2019). Therefore, I argue that including a neutral mindset condition is not required to control for the increased workload of the deliberative and implemental mindset tasks. The effects of time, workload, and fatigue seem negligible (see also the Methods section of Experiment 2, for a more elaborate discussion of this issue).

**Experimental manipulation: Incentives.** Prior to working on the decision task, participants were randomly assigned to one of the two incentive conditions (fixed rate vs. performance-based) and accordingly informed about the bonus payment modalities. That is, participants in the fixed rate condition were informed that they would receive a fixed bonus payment (“You will receive a fixed bonus of £0.80”). In the performance-based incentive condition, the bonus payment was contingent on the performance in the decision task (“You will receive a bonus of £0.10 for each correct response in this part”). In both conditions, participants were given feedback on the number of correct responses after they had answered all decision problems.
**Decision task.** The decision task consisted of 15 decision problems. Five problems measured cognitive reflection (CRT; Frederick, 2005; Toplak et al., 2014), the remaining ten problems were binary choice probability judgment problems. These included five base-rate neglect problems (see, for instance, Pennycook & Thompson, 2017), and five conjunct probability problems (see Fisk, 2017). These ten problems were summarized as the probability judgment task since both types of decision problems reflected decision processes of probabilistic reasoning. The probability judgment task problems were compiled from the literature (De Neys & Glumicic, 2008; Ferreira, Garcia-Marques, Sherman, & Sherman, 2006; Tversky & Kahneman, 1974), some of the problems were own developments designed for a different study (Ludwig, Ahrens, & Achtziger, in press). For a full list of decision problems and more information about the sources, see Appendix A.

The CRT decision problems were presented as questions with open response format (between 22 and 61 words). Participants were instructed to enter exclusively numerical values when responding to these questions (“Please enter digits only”). Probability judgment problems were short situational descriptions (between 48 and 112 words), followed by the question “Which of the following is more likely?” (base-rate neglect problems), or a problem-specific variation thereof (in conjunct probability problems, e.g., “Which option should the company choose?”). Responding to the probability judgment problems, participants indicated their preference for a choice option by clicking on one of two response buttons presented below the question. The decision problems were presented in fully randomized order, the order of choice options was also fully randomized for all participants (i.e., Choice A left and Choice B right, or the reverse).

The probability judgment task was used because base-rate neglect problems and conjunct probability problems represented standard decision problems from the judgment and decision making literature. They were also used extensively in the heuristics and biases research program (e.g., Tversky & Kahneman, 1974) and can thus be considered as well-established, classic decision problems. These problems are typically moderately difficult and often elicit erroneous responses. Errors may arise in these problems because, typically, the correct response conflicts with another response which is favored intuitively. For instance, in base-rate neglect problems, the erroneous response may seem
intuitively attractive because it is consistent with widespread stereotypes about, e.g., certain professions (lawyers, engineers) or age groups (see Pennycook & Thompson, 2017, for a more comprehensive review of the definitory characteristics of base-rate neglect problems). Giving the correct response to such problems, then, usually requires some degree of probabilistic reasoning and the integration of all information available in the description. Hence, the probability judgment problems facilitated the examination of decision errors arising from the conflict of different decision processes, and it could be expected that participants would indeed produce a number of errors when responding to these problems. This was important because it ensured that some performance variance would occur in the decision task, affording some space for performance improvements through financial incentives and the deliberative and implemental mindsets.

The CRT (Frederick, 2005; Toplak et al., 2014) is widely considered as a reliable measure of general susceptibility to decision biases, or in other words, an individual’s propensity to give intuitive responses. Conversely, it is often interpreted as a measure for an individual’s propensity to override intuitive (but faulty) responses to challenging decision problems. As such, it served as a potent predictor of performance in classic heuristics and biases tasks (e.g., Toplak, West, & Stanovich, 2011; but see also Alós-Ferr, Garagnani, & Hügelschäfer, 2016; Alós-Ferr & Hügelschäfer, 2016, reporting mixed results regarding the CRT’s predictive validity in these tasks). Like the probabilistic reasoning problems, the CRT decision problems typically elicit errors based on faulty intuitions, and some deliberation is required to arrive at the correct response.

The original three-item scale by Frederick (2005) has become hugely influential in the past years as an individual difference measure of cognitive reflection. Its popularity and massive use in a variety of laboratory, field, and web-based studies has raised the public awareness about the construct, not least about its most famous item, the bat-and-ball problem, which has also been cited numerous times in the media and popular literature (e.g., Kahneman, 2012). Several expansions are currently available to counteract the increasing awareness of the CRT items in the general population (Primi, Morsanyi, Chiesi, Donati, & Hamilton, 2016; Thomson & Oppenheimer, 2016; Toplak et al., 2014). Since prior knowledge of the CRT decision problems may seriously contaminate its validity as a measure of cognitive reflection (see also Haigh, 2016), and because the items (and the correct responses) are easily traceable on the internet, it was
imperative to introduce changes to the original items for the use in Experiments 1a and 1b. Therefore, the decision problems were adapted for the use in the scope of the present dissertation in order to preserve the CRT’s validity. These changes effectively rendered these five items new decision problems (and the correct responses undetectable in the internet; see Appendix A for the full list of CRT items), although the general structure and objective of the original CRT items remained intact. Hence, a by-product of Experiments 1a and 1b is the development of yet another extension to the original CRT.

**Further measures.** After completion of the decision task, participants indicated their age, sex, whether English was their first language, and prior knowledge of the problems used in the decision task. Participants who indicated prior knowledge of more than three out of the 15 decision problems and participants whose first language was not English were excluded from the analysis. Several additional items were included to serve as a mindset manipulation check (see V. Brandstätter & Frank, 2002). Specifically, participants in the deliberative and implemental mindset conditions (but not control participants) self-reported on their commitment to their personal concern or project as described in the mindset induction task, determination to act according to their considerations, and overall decidedness, i.e., the subjective temporal distance from the moment of making a decision.

It could be expected that commitment, determination to act, and decidedness would be determined by the deliberative and implemental mindsets (see V. Brandstätter & Frank, 2002; Gollwitzer, 2012). Relative to participants in a deliberative mindset, implemental participants should score higher on these three variables. This is because the implemental mindset, as opposed to the deliberative mindset, signals a post-decisional state of mind which supports goal striving by increasing goal commitment and determination to translate intentions into action.

The measure of commitment (five items, Cronbach’s $\alpha = .74$) used a five-point Likert scale from 0 to 4, e.g., “Quite frankly, I don’t care if I achieve it or not” (Klein, Wesson, Hollenbeck, Wright, & DeShon, 2001). Determination to act was measured with two items (Spearman-Brown $\rho = .79$) on a nine-point Likert scale from 0 to 8; “Do you know when, where, and how to act according to your considerations?” and “How determined are you to act according to your considerations?” Decidedness was assessed
in terms of a timeline from “pre-decisional” to “post-decisional”, on which the midpoint (the starting point of the slider from 0 to 100) indicated the moment of making a decision. In addition, participants in the performance-based incentive condition indicated the valence of the monetary reward (three items on a nine-point Likert scale from 0 to 8, $\alpha = .79$; e.g., “How attractive was it for you to earn money contingent on correct responses?”).

**Results**

This section reports the results of the statistical analyses. First, I will evaluate the success of the mindset manipulation based on the self-report measures of commitment, determination to act, and decidedness. Next, I will outline the analytical approach to examining decision task performance (number of correct responses, decision times) before presenting the results separately for CRT and probability judgment problems. The analyses of sum scores of correct responses in the decision task mainly rely on proportional odds logistic regression, while decision times were analyzed using linear mixed-effect models. Finally, I will turn to the analysis of the cheating behavior proxy.

**Manipulation check.** To check the quality of the mindset induction, the two mindset conditions (deliberative vs. implemental) were compared with regard to the participants’ commitment, determination to act, and decidedness. Since prior work had indicated interactions of the deliberative and implemental mindsets and sex (Hügelschäfer & Achtziger, 2014), the participants’ sex, and the interaction of mindset and sex were added as additional control variables. Three separate 2 (between, mindset) × 2 (between, sex) analyses of variance on the mindset manipulation check variables indicated that mindsets affected commitment, determination, and decidedness.

As expected, implemental participants scored higher on all three measures. Commitment was increased in the implemental mindset compared with the deliberative mindset ($M_{\text{del}} = 2.81, SD = 0.64; M_{\text{imp}} = 3.39, SD = 0.63$), $F(1, 181) = 39.57, p < .001, \eta^2 = .171$. Determination to act was also higher for implemental than for deliberative participants ($M_{\text{del}} = 5.52, SD = 1.59; M_{\text{imp}} = 6.64, SD = 1.35$), $F(1, 181) = 27.10, p < .001, \eta^2 = .131$. Finally, implemental participants indicated higher levels of decidedness
(\(M_{\text{sel}} = 40.14, SD = 20.33; M_{\text{imp}} = 57.82, SD = 24.06\)), \(F(1, 181) = 29.76, p < .001, \eta^2 = .139\). There were no effects of sex on commitment, \(F(1, 181) = 1.03, p = .311\), or determination, \(F(1, 181) = 0.10, p = .757\), but a marginally significant effect of sex on decidedness (\(M_{\text{female}} = 52.06, SD = 23.45; M_{\text{male}} = 45.36, SD = 24.18\)), \(F(1, 181) = 3.67, p = .057, \eta^2 = .020\). This suggested that females, on average, tended to be more decided with respect to their personal concerns or projects than males. The interaction of mindset and sex was not significant for commitment, \(F(1, 181) = 2.36, p = .127\), and only marginally significant for determination, \(F(1, 181) = 2.79, p = .096, \eta^2 = .015\), and decidedness, \(F(1, 181) = 2.88, p = .092, \eta^2 = .016\), suggesting that the mindset effect on both determination and decidedness was slightly stronger for females than for males.

The mindset conditions differed significantly in terms of commitment, determination to act, and decidedness, consistent with the predicted direction of these effects. Hence, it could be concluded that the deliberative and implemental mindsets were successfully induced by the procedure used in this study.\(^2\) The manipulation of mindsets worked as intended.

**Preparations and analytical approach.** Reliability analyses of the sum scores for the CRT and the probability judgment problems indicated that the internal consistency of these measures (as indicated by Cronbach’s \(\alpha\)) remained below desirable levels. The reliability analysis further suggested to drop items from both scales in order to increase the reliability. For the CRT, the reliability analysis indicated that the reliability could be increased to \(\alpha = .73\) by dropping one item (the watch problem, see Appendix A). For the probability judgment index, Cronbach’s \(\alpha\) was poor when including all ten items but could

\(^2\)As an additional manipulation check, the information provided in the mindset induction tasks was content-analyzed. Two independent raters categorized the participants’ statements regarding the overall quality (i.e., the degree to which participants faithfully deliberated their concern or planned their project), the affective valence of the statements, and the type of personal problem (e.g., professional or interpersonal). As could be expected, participants working on the deliberative mindset task referred more often to interpersonal problems (e.g., family or romantic partners) and put more emphasis on the affective aspects of their concerns than did participants working on the implemental mindset task. Controlling for these differences did not change the results in the subsequent decision task. Females and males did not differ regarding the overall quality, affective valence, or type of personal issue.
be raised to acceptable levels, $\alpha = .62$, when dropping two of the conjunct probability problems (the soccer, gamble problems) and one base-rate neglect problem (the Africa problem). To ensure the highest possible reliability of these measures, I proceeded accordingly and dropped the three items. Thus, the results reported hereafter were based on sum scores computed from four items (CRT) and seven items (probability judgment), respectively.

Sum scores of the CRT (based on four items) and the probability judgments (based on seven items) were analyzed using hierarchical ordered logistic regressions. The CRT and probability sum scores of correct responses were considered as categorical variables, not continuous ones, so ordered logistic or probit regression was necessary to appropriately fit the regression models. To enhance the interpretability of the regression coefficients, I fitted ordered logistic regressions (specifically, proportional odds logistic regression models), which can be interpreted to model log odds, and thus, facilitated the report of odds ratios in addition to the regression coefficients. The analyses were conducted in R using the polr function from the MASS package (R Core Team, 2016; Venables & Ripley, 2002). The same procedure was used to analyze the number of clicks outside the current browser tab as a proxy for cheating behavior during the decision task.

Following a hierarchical procedure, the predictors were added stepwise, block by block. I first fitted an ordered logistic regression model with only the experimental manipulations of mindset (control vs. deliberative vs. implemental) and incentive (fixed rate vs. performance-based) as predictors (Model 1). In a second step, I added the demographic variables age and sex (Model 2). Third, the cheating behavior proxy (i.e., the count of clicks outside the current browser tab) was added as a predictor (Model 3). Finally, I added the interactions of mindset and incentive were added to the model (Model 4).³

Comparative model fit was assessed by Akaike Information Criteria (AIC) for each of the models. That is, the best fitting model was determined as the one with the smallest AIC, out of the four models compared. Blocks of predictors were retained for

³ Initially, the interaction of mindset and sex was added in a fifth step. However, mindsets and sex did not interact in predicting any of the dependent variables. Therefore, the interaction term was dropped and the model comparison was limited to four models.
the next step only if the difference in the AICs between the last best fitting model and the model including the current block of predictors in question was < 2 (see Burnham & Anderson, 2002, pp. 70–72). If the difference in AICs was > 2, i.e., the AIC increased by more than 2 when adding predictors, these variables were not retained for the respective next step.

Note that in the case of decision times, the trial level responses were of interest. That is, the dependent variable was not aggregated per participant (as done in the case of correct responses). To model decision times on the trial level, mixed-effects models with random intercepts for participants and decision problem seemed appropriate (Bates, Mächler, Bolker, & Walker, 2015). The unique advantage of mixed-effects models over, for instance, repeated measures analysis of variance, was that the former facilitated an appropriate statistical approach to the hierarchical data structure (i.e., dissociable types of decisions nested in groups of participants in different experimental conditions). Including the random effects of participants and decision problems furthermore accounted for the variability of decision times based on, e.g., different word lengths of the decision problems, or individual differences in responding comparatively slow or fast to these types of decision problems.

The mixed-effects model analyses were run in R, using the \texttt{lmer} function from the package \texttt{lme4} (Bates et al., 2015). Like the analyses of correct responses, I followed a block-wise step-up procedure. The baseline model (Model 1) included only the fixed effects of the experimental manipulations of mindset and incentive, the fixed effect of problem type (CRT vs. probability judgment), and the random effects of participants and decision problems. To these fixed and random effects, I added the fixed effects of the demographic variables age and sex (Model 2), the fixed effect of cheating (Model 3), and the fixed effects of the mindset interactions with the incentive factor (Model 4). Again, models were compared in terms of their AIC to assess model fit, and blocks of predictors were retained for the next step only if the difference in AICs from the previous best fitting model to the current one was < 2.

**Correct responses.** Mean sum scores for correct responses in the CRT and the probability judgment task are shown in Figure 2. I first analyzed the CRT sum scores, following the hierarchical block-wise procedure described above. Complete reports for
all four models are given in Table 2. The best fitting model was Model 2, including the experimental factors mindset and incentive, as well as the demographic variables age and sex. This model indicated significant increases of CRT scores for participants in the performance-based incentive condition and for males, as well as a marginally significant effect of age. Accordingly, for participants in the performance-based incentive condition, the odds of scoring higher on the CRT were 1.65 times the odds of participants in the fixed rate condition (ceteris paribus). This finding supported the hypothesis H1 that performance-based incentives, relative to fixed rate payments, improve performance in economic decision tasks. Holding all other variables constant, the odds of scoring higher on the CRT for males were 2.71 times the odds for females. Regarding the effect of age, for an increase of one year, the odds of scoring higher on CRT were multiplied by 1.02 (i.e., an increase of 2%), holding constant all other variables. Based on Model 2, the deliberative and implemental mindsets and cheating behavior did not significantly affect CRT sum scores. Thus, the hypotheses H5 (the deliberative mindset improves performance) and H8 (the implemental mindset impairs performance) were not supported.

Figure 2. Mean sum scores of correct responses in the CRT and the probability judgment task across mindset and incentive conditions in Experiment 1a. Error bars indicate standard errors of the mean.
Table 2

Results of the proportional odds logistic regression on correct responses in the CRT (Experiment 1a).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>Odds ratio [.95 CI]</td>
<td>b</td>
<td>Odds ratio [.95 CI]</td>
</tr>
<tr>
<td>Deliberative</td>
<td>0.016</td>
<td>1.02 [0.62, 1.66]</td>
<td>0.109</td>
<td>1.11 [0.68, 1.83]</td>
</tr>
<tr>
<td>(SE)</td>
<td>0.251</td>
<td></td>
<td>0.256</td>
<td></td>
</tr>
<tr>
<td>Implemental</td>
<td>-0.059</td>
<td>0.94 [0.58, 1.55]</td>
<td>0.032</td>
<td>1.03 [0.63, 1.70]</td>
</tr>
<tr>
<td>(performance)</td>
<td>(0.252)</td>
<td></td>
<td>(0.256)</td>
<td></td>
</tr>
<tr>
<td>Incentive</td>
<td>0.300</td>
<td>1.35 [0.90, 2.03]</td>
<td>0.502**</td>
<td>1.65 [1.08, 2.52]</td>
</tr>
<tr>
<td>(SE)</td>
<td>0.208</td>
<td></td>
<td>(0.215)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.018*</td>
<td>1.02 [1.00, 1.04]</td>
<td>0.018**</td>
<td>1.02 [1.00, 1.04]</td>
</tr>
<tr>
<td>(SE)</td>
<td>(0.009)</td>
<td></td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Sex (male)</td>
<td>0.998***</td>
<td>2.71 [1.76, 4.17]</td>
<td>0.958***</td>
<td>2.61 [1.67, 4.07]</td>
</tr>
<tr>
<td>(SE)</td>
<td>(0.220)</td>
<td></td>
<td>(0.228)</td>
<td></td>
</tr>
<tr>
<td>Cheating</td>
<td>0.031</td>
<td>1.03 [0.94, 1.13]</td>
<td>0.036</td>
<td>1.04 [0.95, 1.14]</td>
</tr>
<tr>
<td>(SE)</td>
<td>(0.046)</td>
<td></td>
<td>(0.047)</td>
<td></td>
</tr>
<tr>
<td>Incentive × Deliberative</td>
<td>0.909*</td>
<td>2.48</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(SE)</td>
<td>(0.514)</td>
<td></td>
<td>(0.91, 6.79)</td>
<td></td>
</tr>
<tr>
<td>Incentive × Implemental</td>
<td>0.306</td>
<td>1.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(SE)</td>
<td>(0.509)</td>
<td></td>
<td>(0.50, 3.69)</td>
<td></td>
</tr>
</tbody>
</table>

AIC 937.4 918.2 919.8 920.6

Note. * p < .10, ** p < .05, *** p < .01; intercepts dropped for enhanced readability.

It is noteworthy, however, that Model 4 revealed a tendency of an interactive effect between the deliberative mindset and the incentive conditions. Even though this model (Model 4) had a slightly worse fit than the best fitting one (Model 2), the marginally significant interaction of mindset and incentive suggested that the overall effect of the performance-based incentive in improving performance was driven largely by the deliberative mindset condition. This result provided partial support for the hypothesis H11 which predicted an interaction of the deliberative mindset and financial incentives. Accordingly, CRT performance appeared to increase most notably when the deliberative mindset and performance-based payment were combined, but the number of
correct responses seemed unaffected by the deliberative mindset if no incentive was offered. This was also true for the control condition and the implemental mindset, in which performance seemed stable regardless of the incentive condition (see also Figure 2).

Table 3

Results of the proportional odds logistic regression on correct responses in the probability judgment task (Experiment 1a).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
<th>Model 4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
</tr>
<tr>
<td>Deliberative</td>
<td>0.201</td>
<td>1.22 [0.74, 2.01]</td>
<td>0.181</td>
<td>1.20 [0.73, 1.98]</td>
<td>0.198</td>
<td>1.22 [0.74, 2.01]</td>
<td>0.441</td>
<td>1.55 [0.77, 3.12]</td>
</tr>
<tr>
<td>Implemental</td>
<td>0.212</td>
<td>1.24 [0.76, 2.01]</td>
<td>0.192</td>
<td>1.21 [0.74, 1.98]</td>
<td>0.201</td>
<td>1.22 [0.75, 2.00]</td>
<td>0.335</td>
<td>1.42 [0.72, 2.81]</td>
</tr>
<tr>
<td>Incentive</td>
<td>0.614***</td>
<td>1.85 [1.23, 2.78]</td>
<td>0.592***</td>
<td>1.81 [1.19, 2.75]</td>
<td>0.612***</td>
<td>1.84 [1.22, 2.78]</td>
<td>0.870**</td>
<td>2.39 [1.20, 4.74]</td>
</tr>
<tr>
<td>(performance)</td>
<td>(0.209)</td>
<td>[0.98, 1.01]</td>
<td>(0.214)</td>
<td>[1.09, 1.57]</td>
<td>(0.209)</td>
<td>[1.39, 2.78]</td>
<td>(0.350)</td>
<td>[1.12, 4.74]</td>
</tr>
<tr>
<td>Age</td>
<td>0.007</td>
<td>1.00 [0.98, 1.01]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (male)</td>
<td>0.032</td>
<td>1.03 [0.68, 1.57]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cheating</td>
<td>-0.019</td>
<td>1.00 [0.93, 1.12]</td>
<td>0.018</td>
<td>1.02 [0.93, 1.11]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incentive × Deliberative</td>
<td></td>
<td>-0.498</td>
<td>0.61 [0.22, 1.65]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incentive ×</td>
<td></td>
<td>-0.309</td>
<td>0.73 [0.28, 1.96]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implemental</td>
<td></td>
<td>0.019</td>
<td>1.02 [0.93, 1.12]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>1080.0</td>
<td>1083.2</td>
<td>1081.8</td>
<td>1084.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. * p < .10, ** p < .05, *** p < .01; intercepts dropped for enhanced readability.

The picture was rather different for performance in the probability judgment task. Model comparisons (see Table 3 for detailed reports of all four models) indicated that the best fitting model was Model 1, including no further predictors beyond the experimental manipulations of mindset and incentive. Like the CRT performance, the number of correct responses in the probability judgment task was predicted by performance-based
incentives, consistent with H1. The model indicated that for participants in the performance-based incentive condition, the odds of scoring higher in the probability judgment task were 1.85 times the odds of the participants in the fixed rate condition (see also Figure 2). Performance in this task was not affected by age or sex. Hence, the number of correct responses was predicted by age and sex in the CRT but not in the probability judgment task. Again, mindsets did not determine performance in the decision task. Hence, there was no support for H5 and H8. No interactions of mindsets and incentives were observed, and neither did cheating influence performance in the probability judgment task.

**Decision times.** Decision times were analyzed on the level of trials, using mixed-effect model analysis to account for the variability between participants and decision problems. The natural logarithm of the decision times was calculated to reduce the skewness of their distribution. Decision times were trimmed prior to the analyses. Specifically, all trials with decision times three standard deviations above or below the mean of the logged decision time distribution were excluded from the analyses. This resulted in the exclusion of 85 trials (2.6% of all trials).

The full model comparisons for the decision time analysis, following the procedure described above, are given in Table 4. Controlling for the variability between decision problems, there was no difference between CRT and probability judgment items in any of the models. Overall, Model 3 provided the best fit to the data, indicating that the cheating behavior proxy, age, and performance-based incentivization increased decision times. In more detail, an increase of one unit in the cheating proxy (i.e., one additional click outside the current browser tab) was associated with an increase of log decision times of 0.051, .95 confidence interval [0.03, 0.07]. This effect was not surprising, given that more time was required if participants searched online for the correct responses to the decision problems. Hence, this finding validated the use of this measure as a proxy for cheating behavior.

The marginally significant effect of the performance-based incentive suggested that decision times increased by 0.083 [-0.01, 0.18] when the payment was contingent on performance in the decision task. This finding was consistent with the hypothesis H2 that decision times would increase in the case of performance-based incentives. Hence,
providing performance-based incentives slowed down decisions, as could be expected if participants invested more cognitive effort in the task. Neither mindsets, nor their interactions with incentives, predicted decision times in Model 3. Hence, the hypotheses H6 (the deliberative mindset increases decision times) and H9 (the implemental mindset decreases decision times) were not supported.

Table 4

Results of the linear mixed-effects model on decision times, participants and decision problems entered as random effects (Experiment 1a).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b (SE) .95 CI</td>
<td>b (SE) .95 CI</td>
<td>b (SE) .95 CI</td>
<td>b (SE) .95 CI</td>
</tr>
<tr>
<td>Intercept</td>
<td>3.428*** (0.093)</td>
<td>3.252*** (0.124)</td>
<td>3.149*** (0.123)</td>
<td>3.105*** (0.127)</td>
</tr>
<tr>
<td>Problem type (Prob. Judg.)</td>
<td>-0.161 (0.100)</td>
<td>-0.161 (0.101)</td>
<td>-0.161 (0.101)</td>
<td>-0.161 (0.101)</td>
</tr>
<tr>
<td></td>
<td>-0.36, 0.04</td>
<td>-0.36, 0.04</td>
<td>-0.36, 0.04</td>
<td>-0.36, 0.04</td>
</tr>
<tr>
<td>Deliberative</td>
<td>-0.051 (0.061)</td>
<td>-0.041 (0.060)</td>
<td>-0.041 (0.058)</td>
<td>-0.023 (0.082)</td>
</tr>
<tr>
<td></td>
<td>-0.17, 0.07</td>
<td>-0.16, 0.08</td>
<td>-0.15, 0.07</td>
<td>-0.18, 0.14</td>
</tr>
<tr>
<td>Implemental</td>
<td>0.093 (0.060)</td>
<td>0.105* (0.060)</td>
<td>0.105* (0.058)</td>
<td>0.180** (0.080)</td>
</tr>
<tr>
<td></td>
<td>-0.03, 0.21</td>
<td>-0.01, 0.22</td>
<td>-0.03, 0.19</td>
<td>0.02, 0.34</td>
</tr>
<tr>
<td>Incentive (performance)</td>
<td>0.078 (0.050)</td>
<td><strong>0.101</strong> (0.050)</td>
<td><strong>0.083</strong> (0.049)</td>
<td><strong>0.160</strong> (0.079)</td>
</tr>
<tr>
<td></td>
<td>-0.02, 0.18</td>
<td>0.00, 0.20</td>
<td>-0.01, 0.18</td>
<td>0.01, 0.32</td>
</tr>
<tr>
<td>Age</td>
<td>0.003 (0.002)</td>
<td>0.004** (0.002)</td>
<td>0.004** (0.002)</td>
<td>0.005** (0.002)</td>
</tr>
<tr>
<td></td>
<td>0.00, 0.01</td>
<td>0.00, 0.01</td>
<td>0.00, 0.01</td>
<td>0.00, 0.01</td>
</tr>
<tr>
<td>Sex (male)</td>
<td><strong>0.111</strong> (0.050)</td>
<td>0.048 (0.050)</td>
<td>-0.05, 0.15</td>
<td>0.045 (0.050)</td>
</tr>
<tr>
<td></td>
<td>0.01, 0.21</td>
<td><strong>0.051</strong>* (0.011)</td>
<td>-0.05, 0.15</td>
<td>-0.05, 0.14</td>
</tr>
<tr>
<td>Cheating</td>
<td></td>
<td></td>
<td><strong>0.050</strong>* (0.011)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.03, 0.07</td>
<td>0.03, 0.07</td>
</tr>
<tr>
<td>Incentive × Deliberative</td>
<td></td>
<td></td>
<td>-0.035 (0.115)</td>
<td>-0.26, 0.19</td>
</tr>
<tr>
<td>Incentive × Implemental</td>
<td></td>
<td></td>
<td><strong>-0.206</strong> (0.115)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.43, 0.02</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>5056.5</td>
<td>5053.7</td>
<td><strong>5033.6</strong></td>
<td>5034.1</td>
</tr>
</tbody>
</table>

Note. *p < .10, **p < .05, ***p < .01.
An interesting observation can be made when comparing Model 2 to Model 3. Based on the former, one could argue that males seem to take significantly longer than females to make decisions in the CRT and probability judgment task. However, in Model 3, the cheating behavior proxy was added and this gender difference disappeared. This suggested that males engaged more in cheating and that increased decision times were driven by searching for information outside the current browser tab, rather than by actual decision times differences between males and females.

Also interesting, Model 4 pointed to an interaction of mindsets and incentives, providing preliminary support for the hypothesis H11. Note that this model performed slightly worse in terms of AIC. However, the increase in AIC from Model 3 to Model 4 was < 2, so there is a good reason to also consider the effects as estimated by Model 4 (Burnham & Anderson, 2002). The marginally significant interaction between the implemental mindset and the performance-based incentive suggested that the implemental mindset slowed down decisions compared with the control condition and deliberative mindset (in contrast to the hypothesis H9), but this was only the case if the payment was fixed. When performance-based incentives were offered, there was a tendency of the implemental mindset to expedite decisions (consistent with H9). This observation may be interpreted as initial evidence for a meaningful interaction of mindsets and incentives, albeit different from the predictions formulated above.

**Cheating.** The number of clicks outside the current browser tab, i.e., the cheating behavior proxy, was also analyzed as a dependent variable. Again, an ordered logistic regression was used to model this variable, following the same procedure as before. The summary for all models is displayed in Table 5. In line with the assumption inferred from the decision time data, males were more prone to cheating than females. Specifically, the odds for males to cheat more were 3.34 times the odds for females, ceteris paribus. The analyses further indicated that the second model best fitted the data, indicating significant effects of the implemental mindset and age. For participants in an implemental mindset, the odds for more cheating were 2.22 times the odds of the control condition, all other variables held constant. Age was associated with fewer cheating. An increase of one year decreased cheating by 2.7% (OR = 0.973), held constant all other variables.
Although Model 3, including the interaction of mindset and incentive, performed slightly worse than Model 2 in terms of AIC (but note, again, that the increase in AIC from Model 2 to Model 3 was < 2), it merits a closer look. Model 3 revealed a marginally significant interaction of the implemental mindset with performance-based incentivization. Specifically, this effect indicated that cheating was increased in the implemental mindset when the payment was fixed, but decision makers cheated less than individuals in the control condition and deliberative mindset when the incentive was contingent on their performance in the decision task.

Table 5
Results of the proportional odds logistic regression on the sum of clicks outside the current browser tab during the decision task (Experiment 1a).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>Odds ratio [95 CI]</td>
<td>b</td>
<td>Odds ratio [95 CI]</td>
<td>b</td>
<td>Odds ratio [95 CI]</td>
</tr>
<tr>
<td>Deliberative</td>
<td>0.453</td>
<td>1.57 [0.89, 2.77]</td>
<td>0.401</td>
<td>1.49 [0.83, 2.69]</td>
<td>0.748*</td>
<td>2.11 [0.90, 4.99]</td>
</tr>
<tr>
<td>Implemental</td>
<td>0.747**</td>
<td>2.11 [1.21, 3.69]</td>
<td>0.795**</td>
<td>2.22 [1.24, 3.95]</td>
<td>1.293***</td>
<td>3.65 [1.61, 8.25]</td>
</tr>
<tr>
<td>Incentive (performance)</td>
<td>0.068</td>
<td>1.07 [0.68, 1.68]</td>
<td>0.156</td>
<td>1.17 [0.73, 1.88]</td>
<td>0.753*</td>
<td>2.12 [0.90, 5.04]</td>
</tr>
<tr>
<td>Age</td>
<td>-0.027**</td>
<td>0.97 [0.011, 0.99]</td>
<td>-0.027**</td>
<td>0.97 [0.011, 0.99]</td>
<td>1.207***</td>
<td>3.34 [0.95, 0.99]</td>
</tr>
<tr>
<td>Sex (male)</td>
<td>1.207***</td>
<td>3.34 [2.07, 5.41]</td>
<td>1.197***</td>
<td>3.31 [2.04, 5.37]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incentive ×</td>
<td>-0.665</td>
<td>0.51 [0.603, 0.68]</td>
<td>0.113</td>
<td>0.51 [0.01, 1.13]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deliberative</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incentive ×</td>
<td>-1.038*</td>
<td>0.35 [0.594, 0.89]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implemental</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

AIC 882.8 852.4 853.3

Note. * p < .10, ** p < .05, *** p < .01; intercepts dropped for enhanced readability.

Note that this finding is also in line with the observed interaction of mindsets and incentives in determining decision times. If paid a fixed rate, decision makers in an
implemental mindset engaged in the search for information outside the current browser tab to a greater extent, and this presumably drove decision times. When offered performance-based incentives, implemental participants engaged less in information search outside the current browser tab and therefore made faster decisions on average. However, it should be noted that the interactive effect of mindsets and incentives on decision times remained marginally significant even when controlling for the amount of cheating (see Table 3, Model 4). Thus, reduced cheating in the implemental mindset when payment was contingent on performance can explain some variation in the decision times, but there may still be an interaction of these factors that cannot be explained by cheating.

Discussion

The results from Experiment 1a can be summarized in terms of three main findings. First, the hypotheses H1 and H2 received robust support. This finding confirmed that performance-based incentivization, relative to a fixed rate payment, increased effort and performance in economic decision tasks. Participants in the performance-based incentive condition performed significantly better in the CRT and the probability judgment task, i.e., they provided more correct responses to the decision problems. To the extent that decision times reflected the effort invested in the task, it was shown that effort was increased when decision makers were offered monetary rewards contingent on their performance. The finding that decision times increased and performance improved under incentivization supported the idea that the beneficial effects of financial incentives on economic performance were, at least in part, mediated by effort. Hence, there was evidence for the incentive-effort-performance relation as usually assumed in experimental economic research.

Second, there were no direct effects of the deliberative and implemental mindsets on performance or decision times. This was equally true for both the CRT and the probability judgment task. The hypotheses H5, H6, H8, and H9 were thus not supported. But several findings suggested that mindsets interacted with financial incentives in determining performance and decision times. In particular, there was preliminary evidence in line with the hypothesis H11, suggesting that CRT performance was significantly increased in the deliberative mindset only when performance-based
incentives were offered. Also, in line with H11, the implemental mindset was associated with faster decisions only when performance was incentivized.

Third, the measure used for approximating cheating behavior, i.e., the number of clicks outside the current browser tab, yielded several important insights. It was discovered that decision makers in an implemental mindset were less prone to engaging in cheating behavior only when performance-based incentives were offered. But if the payment was fixed, the implemental mindset even led to increased cheating, relative to the deliberative mindset and the control condition. This finding presented an interesting question for future research. I will return to this point in the General Discussion of Experiments 1a and 1b.

Taken together, there was robust evidence for the beneficial effects of performance-based financial incentives on performance and decision times. This was consistent with the notion of increased effort as the main driver behind these effects of financial incentives on economic performance. While there were no mindset effects, initial evidence suggested that mindsets may interact with incentives in determining performance, decision times, and the decision makers’ willingness to cheat in the task.

An additional finding was that males performed much better than females in the CRT but not in the probability judgment task. This gender difference in the CRT has been observed consistently in prior work (e.g., Alós-Ferrer et al., 2016; Frederick, 2005; Willoh, 2019) and thus came as no surprise. However, it remained an open question whether CRT performance benefits for males were due to differences in (subjective) numeracy. Performance in the CRT presumably relies heavily on numeracy, i.e., the perceived fluency with numerical information (sometimes referred to as quantitative self-efficacy; Welsh, Burns, & Delfabbro, 2013; Zhang, Highhouse, & Rada, 2016). This is because in order to correctly solve these problems, decision makers are required to inhibit intuitive, erroneous responses and actually do some mathematics. That is, decision makers must be willing to and capable of engaging in some basic linear algebra in order to solve these problems correctly. This is not the case, at least not to the same extent, in the probability judgment problems. These decision problems as well involve numerical operations (evaluations of joint versus disjunct probabilities, or sample base-rate probabilities), but the correct response may be inferred from carefully weighing the
evidence for the opposing choice options. Actually performing mathematical operations
is usually not required to arrive at the correct response. Therefore, a measure of subjective
numeracy was added to the post-experimental questionnaire in Experiment 1b to test the
idea that gender differences in the CRT, as observed in Experiment 1a and in prior work
could be explained by numeracy, as suggested by Zhang et al. (2016).

**Experiment 1b**

Except for the added measure of subjective numeracy (see below), Experiment 1b
was very similar to Experiment 1a. The one major difference was that in this experiment,
the effects of the financial incentive were compared between two conditions of
performance-based payment. That is, one group were offered a low and the other a high
payment for each correct response in the decision task. Apart from these two exceptions,
all materials and procedures were the same as in Experiment 1a.

**Method**

**Participants and design.** The experiment had a 3 (between, mindset: control vs.
deliberative vs. implemental) \( \times \) 2 (between, incentive: low vs. high) between-subjects
design with six experimental conditions resulting from crossing the two factors. Again,
performance measures in the decision task (correct responses, decision times) served as
the main dependent variables. Like in Experiment 1a, the number of clicks outside the
current browser tab served as a proxy for cheating behavior.

Prior to data collection, a target sample size of \( N = 300 \) was determined to ensure
a minimum of 50 participants per condition. A larger number of participants was recruited
in order to account for foreseeable exclusions and to meet the target sample size. Hence,
three hundred and seventy-two participants were recruited from the same participant pool
as in Experiment 1a (*Prolific*, [www.prolific.co](http://www.prolific.co), Oxford, UK), but those who participated
in the first study were not allowed to participate in Experiment 1b. The anticipated
average duration and base payment were the same as in the previous experiment (20-25
minutes, £2.30).
In Experiment 1b, participants were randomly assigned to either the high incentive or the low incentive condition. In both conditions, the bonus payment was contingent on the performance in the decision task. In the low incentive condition, participants received £0.05 per correct response in the decision task, while participants in the high incentive condition received £0.20 per correct response. That is, in the high incentive condition, decision makers received four times the amount of money for a correct response, relative to the low incentive condition. Correspondingly, participants could receive up to four times the amount of overall bonus payment in the high incentive condition compared with the low incentive condition (i.e., a maximum of £3 in the high incentive condition versus max. £0.75 in the low incentive condition).

Like in Experiment 1a, several exclusions were required to ensure appropriate data quality. Prior to the analyses, 39 participants were excluded due to several reasons (e.g., missing data, or very low effort in the mindset induction task). The final sample size, on which all analyses were based, was therefore $N = 333$ (103 males; $M_{age} = 33.85$ years, $SD = 12.24$), roughly equally distributed across the mindset conditions: $n_{con} = 99$, $n_{del} = 107$, and $n_{imp} = 127$, respectively, and the two incentive conditions: $n_{low} = 160$ and $n_{high} = 173$.

**Procedure and materials.** The procedure and materials were exactly the same as in Experiment 1a, with only the following two exceptions. First, the experimental manipulation of the incentive differed from the first study. In this experiment, participants were randomly assigned to either a low or a high incentive condition, the bonus payment depended on the number of correct responses in the decision task in both groups. Second, a measure of perceived numerical ability was added to the post-experimental questionnaire, i.e., a subjective numeracy scale assessing the perceived ability to perform mathematical tasks and the preference for the use of numerical versus prose information (eight items, e.g., “How good are you at calculating a 15% tip?”; Fagerlin et al., 2007).

**Results**

**Manipulation check.** As in Experiment 1a, the quality of the mindset induction was assessed by comparing the mindset conditions in terms of commitment (five items,
Cronbach’s $\alpha = .77$), determination to act (Spearman-Brown $\rho = .73$), and decidedness on a temporal dimension from pre-decisional to post-decisional (one item). Three separate 2 (between, mindset) $\times$ 2 (between, sex) analyses of variance were conducted to evaluate the mindset manipulation. Again, it was predicted that participants in an implemental mindset should score higher on these three variables.

As expected, the mindset determined commitment ($M_{\text{del}} = 2.87$, $SD = 0.66$; $M_{\text{imp}} = 3.36$, $SD = 0.64$), $F(1, 230) = 32.46$, $p < .001$, $\eta^2 = .123$, determination to act ($M_{\text{del}} = 5.34$, $SD = 1.48$; $M_{\text{imp}} = 6.42$, $SD = 1.18$), $F(1, 230) = 39.10$, $p < .001$, $\eta^2 = .147$, and decidedness, ($M_{\text{del}} = 39.79$, $SD = 20.03$; $M_{\text{imp}} = 55.43$, $SD = 20.93$), $F(1, 230) = 33.48$, $p < .001$, $\eta^2 = .127$. These mindset effects were consistent with the prediction and comparable in size to those found in Experiment 1a. It could be concluded that the induction of the deliberative and implemental mindsets was successful and worked as intended.\(^4\)

Furthermore, like in Experiment 1a, there was no effect of sex on commitment, $F(1, 230) = 0.01$, $p = .932$. Unlike the previous study, there was no sex difference on decidedness, $F(1, 230) = 0.05$, $p = .821$, but males tended to be more determined to act according to their considerations in the mindset task ($M_{\text{female}} = 5.84$, $SD = 1.55$; $M_{\text{male}} = 6.12$, $SD = 1.09$), $F(1, 230) = 2.12$, $p = .090$, $\eta^2 = .012$. There were no interactions of mindset and sex on any of the manipulation check variables, all $Fs (1, 230) \leq 2.12$, all $ps \geq 147$.

To check the quality of the incentive manipulation (low vs. high), I compared the experimental conditions in terms of the self-reported valence of the incentive (three items, Cronbach’s $\alpha = .76$) by conducting a 3 (between, mindset) $\times$ 2 (between, incentive) $\times$ 2 (between, sex) analysis of variance. Consistent with the aim of the manipulation, the incentive determined valence ($M_{\text{low}} = 6.55$, $SD = 1.83$; $M_{\text{high}} = 6.99$, $SD = 1.70$), $F(1, 326) = 4.70$, $p = .031$, $\eta^2 = .014$. Surprisingly, mindset also affected the incentive valence ($M_{\text{con}} = 7.23$, $SD = 1.59$; $M_{\text{del}} = 6.88$, $SD = 1.77$; $M_{\text{imp}} = 6.51$, $SD = 1.87$), $F(1, 326) = 9.17$, $p = .003$, $\eta^2 = .025$. The main effect of mindset indicated that the incentive valence was decreased in both mindsets relative to the control condition, but

\(^4\) Again, the content analysis of personal concerns or personal projects did not reveal any differences that would affect choices and decision times in the subsequent decision task.
did not differ between the deliberative and implemental mindsets. No interactions were observed.

**Preparations and analytical approach.** Like in Experiment 1a, I first conducted reliability analyses for the CRT and probability judgment sum scores of correct responses. As in the previous study, the analysis suggested rather low reliability for both tasks (as indicated by Cronbach’s $\alpha$). Again, internal consistency could be increased for both scales by dropping single items. For the CRT, the reliability analysis indicated that the internal consistency could be increased to $\alpha = .65$ when dropping one item (the watch problem). This was the same item that was also dropped in the previous study, further corroborating the assumption that it might be rather detrimental to the internal consistency of the CRT. The internal consistency of the four-item CRT remained below the reliability observed in Experiment 1a but can be considered as acceptable. Regarding the probability judgment task, the analysis suggested to drop three items, again the same items that were dropped in the previous experiment (conjunct probability problems: soccer, gamble; base-rate neglect: Africa). Dropping these items raised the internal consistency to $\alpha = .55$. Hence, the reliability of the probability judgment task’s sum score of correct responses remained below the level observed in Study 1a and was questionable in this experiment. Like in the previous study, I dropped the items as suggested by the reliability analysis and computed sum scores from four items (CRT) and seven items (probability judgment), respectively, for further analyses.

The analytical approach corresponded to that of Experiment 1a. That is, hierarchical ordered logistic regressions were conducted for the analyses of correct responses and cheating (aggregated on the level of participants), and mixed-effect models were fitted for the decision time analysis (on the level of trials). Blocks of predictors were added stepwise. First, I fitted a model including only the experimental manipulations of mindset (control vs. deliberative vs. implemental) and incentive (low vs. high) as predictors (Model 1). Second, the demographic variables age and sex were added (Model 2). In a third step, the cheating behavior proxy and numeracy (eight items, Cronbach’s $\alpha = .84$) were added as predictors (Model 3). Finally, the interaction of mindset and incentive was added (Model 4). Like before, comparative model fit was assessed by means of AIC and blocks of predictors were retained for inclusion in the next-
step model only if the difference in AICs between the last best fitting model and the current model was $< 2$ (see Burnham & Anderson, 2002).

**Correct responses.** The mean sum scores of correct responses in the CRT (based on four items) and the probability judgment task (seven items) across mindsets and incentives are shown in Figure 3. A summary of the model comparisons for the CRT sum score is presented in Table 6. The analysis indicated that Model 3 best fit the data, including the full list of predictors except for the interaction of mindset and incentive. Like in the previous experiment, age and sex determined CRT performance. An increase of one year was associated with odds of scoring higher on the CRT multiplied by 1.02 (i.e., a 2% increase), all other variables held constant. Males performed better in the CRT than females, the odds for males of scoring higher were 1.53 times the odds for females.

![Figure 3](image)

*Figure 3.* Mean sum scores of correct responses in the CRT and the probability judgment task across mindset and incentive conditions in Experiment 1b. Error bars indicate standard errors.

Note that the gender difference in CRT performance was still significant when controlling for numeracy. Numeracy was added in Model 3 and turned out to be a significant predictor of CRT sum scores. For an increase of one unit in numeracy (on the
scale from one to six), the odds of scoring higher on the CRT were multiplied by 1.80, all other variables held constant. While controlling for numeracy considerably reduced the CRT performance difference between males and females (OR = 1.53 in Experiment 1b, compared with OR = 2.71 in Experiment 1a), males still outperformed females. This finding suggested that the gender difference in CRT performance could only partly be explained by numeracy.

Table 6
Results of the proportional odds logistic regression on correct responses in the CRT (Experiment 1b).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
</tr>
<tr>
<td>Deliberative</td>
<td>0.193</td>
<td>1.21 [0.75, 1.96]</td>
<td>0.196</td>
<td>1.22 [0.75, 1.97]</td>
</tr>
<tr>
<td>Implemental</td>
<td>-0.324</td>
<td>0.72 [0.45, 1.16]</td>
<td>-0.311</td>
<td>0.73 [0.46, 1.18]</td>
</tr>
<tr>
<td>Incentive (low)</td>
<td>0.012</td>
<td>1.01 [0.69, 1.48]</td>
<td>0.072</td>
<td>1.07 [0.73, 1.58]</td>
</tr>
<tr>
<td>Age</td>
<td>0.014*</td>
<td>1.01 [1.00, 1.03]</td>
<td>0.017**</td>
<td>1.02 [1.00, 1.03]</td>
</tr>
<tr>
<td>Sex (male)</td>
<td>0.862***</td>
<td>2.37 [1.55, 3.62]</td>
<td>0.425*</td>
<td>1.53 [0.97, 2.41]</td>
</tr>
<tr>
<td>Cheating</td>
<td></td>
<td></td>
<td>0.088**</td>
<td>1.09 [1.01, 1.18]</td>
</tr>
<tr>
<td>Numeracy</td>
<td>0.589***</td>
<td>1.80 [1.46, 2.22]</td>
<td></td>
<td>0.598***</td>
</tr>
<tr>
<td>Incentive × Deliberative</td>
<td>-0.262</td>
<td>0.77 [0.29, 2.05]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incentive × Implemental</td>
<td>0.591</td>
<td>1.81 [0.68, 4.76]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>1046.7</td>
<td>1032.6</td>
<td>999.9</td>
<td>1000.7</td>
</tr>
</tbody>
</table>

Note. * p < .10, ** p < .05, *** p < .01; intercepts dropped for enhanced readability.

Furthermore, in this experiment (as opposed to Experiment 1a) cheating was also a significant predictor of CRT performance. For an increase of one unit (i.e., one
additional click outside the current browser tab), the odds of scoring higher on the CRT were multiplied by 1.08 (i.e., an increase of 8%), holding constant all other variables. This was rather surprising, given that all CRT problems were adapted so that the correct solutions could not be found by an online search. The incentive factor did not predict CRT sum scores, indicating that offering low versus high incentives did not influence the CRT performance (see also Figure 3). Hence, the hypothesis H3 was rejected. Mindsets were also not predictive of CRT performance, as found Experiment 1a, and again inconsistent with the hypotheses H5 and H8.

Table 7
Results of the proportional odds logistic regression on correct responses in the probability judgment task (Experiment 1b).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
<td>b (SE)</td>
<td>Odds ratio [95 CI]</td>
</tr>
<tr>
<td>Deliberative</td>
<td>0.001 (0.252)</td>
<td>1.00 [0.61, 1.64]</td>
<td>-0.025 (0.253)</td>
<td>0.98 [0.59, 1.60]</td>
</tr>
<tr>
<td>Implemental</td>
<td>0.072 (0.234)</td>
<td>1.08 [0.68, 1.70]</td>
<td>0.074 (0.235)</td>
<td>1.08 [0.68, 1.71]</td>
</tr>
<tr>
<td>Incentive (low)</td>
<td>-0.164 (0.194)</td>
<td>0.85 [0.58, 1.24]</td>
<td>-0.133 (0.195)</td>
<td>0.88 [0.60, 1.28]</td>
</tr>
<tr>
<td>Age</td>
<td>-0.009 (0.008)</td>
<td>0.99 [0.98, 1.01]</td>
<td>-0.009 (0.008)</td>
<td>0.99 [0.98, 1.01]</td>
</tr>
<tr>
<td>Sex (male)</td>
<td>0.332 (0.216)</td>
<td>1.39 [0.91, 2.13]</td>
<td>0.130 (0.226)</td>
<td>1.14 [0.73, 1.78]</td>
</tr>
<tr>
<td>Cheating</td>
<td>0.057 (0.040)</td>
<td>1.06 [0.98, 1.14]</td>
<td>0.051 (0.040)</td>
<td>1.05 [0.97, 1.14]</td>
</tr>
<tr>
<td>Numeracy</td>
<td>0.252*** (0.097)</td>
<td>1.29 [1.06, 1.56]</td>
<td>0.263*** (0.097)</td>
<td>1.30 [1.07, 1.57]</td>
</tr>
<tr>
<td>Incentive × Deliberative</td>
<td>-0.969* (0.514)</td>
<td>0.38 [0.14, 1.04]</td>
<td>0.273 (0.476)</td>
<td>0.79 [0.31, 2.02]</td>
</tr>
<tr>
<td>AIC</td>
<td>1200.0</td>
<td>1199.9</td>
<td>1195.3</td>
<td>1195.3</td>
</tr>
</tbody>
</table>

Note. * p < .10, ** p < .05, *** p < .01; intercepts dropped for enhanced readability.
Regarding performance in the probability judgment task, model comparisons indicated that Model 3 provided the best fit to the data. Like for the CRT sum scores, the mindset and incentive factors did not affect performance in the probability judgment problems. Thus, there was no support for the hypotheses H3, H5, and H8. The only significant predictor of probability judgment performance was numeracy, indicating that for an increase of one numeracy unit, the odds of scoring higher in the probability judgment task were multiplied by 1.29 (i.e., an increase of 29%). The detailed report of all models and their comparison is given in Table 7. Consistent with the previous study, age and sex did not influence performance in the probability judgment task.

**Decision times.** Decision times were transformed by calculating the natural logarithm in order to reduce the skewness of the decision time distribution. As in the previous experiment, trials were excluded if the decision time was three standard deviations above or below the mean of the logged decision time distribution. This led to the exclusion of 55 trials (1.5% of all trials).

Decision times were analyzed following the block-wise step-up procedure based on mixed-effect models with random intercepts of participants and decision problems, as described above. The full model comparisons are presented in Table 8. The best fitting model was Model 3, including the full list of predictors except for the interactions of mindsets and incentives. In contrast to Experiment 1a, the type of decision problem determined decision times in this experiment. Probability judgment problems were responded to faster than the CRT problems, log decision times were reduced by -0.186 [-0.39, 0.02] relative to decision times in the CRT. Age also predicted decision times. An increase of one year was associated with an increase in log decision times of 0.005 [0.00, 0.01].
Table 8
Results of the linear mixed-effects model on decision times, participants and decision problems entered as random effects (Experiment 1b).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b$ (SE) .95 CI</td>
<td>$b$ (SE) .95 CI</td>
<td>$b$ (SE) .95 CI</td>
<td>$b$ (SE) .95 CI</td>
</tr>
<tr>
<td>Intercept</td>
<td>$3.550^{***}$ (0.093)</td>
<td>$3.363^{***}$ (0.112)</td>
<td>$3.126^{***}$ (0.137)</td>
<td>$3.177^{***}$ (0.142)</td>
</tr>
<tr>
<td>Problem type (Prob. Judg.)</td>
<td>-0.186* (0.103) -0.39, 0.02</td>
<td>-0.186* (0.103) -0.39, 0.02</td>
<td>-0.186* (0.103) -0.39, 0.02</td>
<td>-0.186* (0.103) -0.39, 0.02</td>
</tr>
<tr>
<td>Deliberative</td>
<td>-0.010 (0.054) -0.12, 0.10</td>
<td>-0.002 (0.053) -0.11, 0.10</td>
<td>0.012 (0.052) -0.09, 0.11</td>
<td>0.012 (0.052) -0.09, 0.11</td>
</tr>
<tr>
<td>Implemental</td>
<td>-0.049 (0.052) -0.15, 0.05</td>
<td>-0.042 (0.051) -0.14, 0.06</td>
<td>-0.018 (0.050) -0.12, 0.08</td>
<td>-0.054 (0.069) -0.19, 0.08</td>
</tr>
<tr>
<td>Incentive (low)</td>
<td>0.015 (0.043) -0.07, 0.10</td>
<td>0.017 (0.042) -0.07, 0.10</td>
<td>0.019 (0.041) -0.06, 0.10</td>
<td>0.061 (0.074) -0.21, 0.08</td>
</tr>
<tr>
<td>Age</td>
<td>0.004** (0.002) 0.00, 0.01</td>
<td>0.005*** (0.002) 0.00, 0.01</td>
<td>0.005*** (0.002) 0.00, 0.01</td>
<td>0.005*** (0.002) 0.00, 0.01</td>
</tr>
<tr>
<td>Sex (male)</td>
<td>0.132*** (0.046) 0.04, 0.22</td>
<td>0.065 (0.047) -0.03, 0.16</td>
<td>0.060 (0.047) -0.03, 0.15</td>
<td>0.060 (0.047) -0.03, 0.15</td>
</tr>
<tr>
<td>Cheating</td>
<td>0.040*** (0.008) 0.02, 0.06</td>
<td>0.041*** (0.008) 0.02, 0.06</td>
<td>0.025 (0.020) -0.01, 0.07</td>
<td>0.025 (0.020) -0.01, 0.07</td>
</tr>
<tr>
<td>Numeracy</td>
<td>0.027 (0.020) -0.01, 0.07</td>
<td>0.025 (0.020) -0.01, 0.07</td>
<td>0.080 (0.099) -0.11, 0.27</td>
<td>0.080 (0.099) -0.11, 0.27</td>
</tr>
<tr>
<td>Incentive × Deliberative</td>
<td>0.154 (0.103) -0.05, 0.36</td>
<td>0.154 (0.103) -0.05, 0.36</td>
<td>0.154 (0.103) -0.05, 0.36</td>
<td>0.154 (0.103) -0.05, 0.36</td>
</tr>
<tr>
<td>Incentive × Implemental</td>
<td>0.080 (0.099) -0.11, 0.27</td>
<td>0.080 (0.099) -0.11, 0.27</td>
<td>0.080 (0.099) -0.11, 0.27</td>
<td>0.080 (0.099) -0.11, 0.27</td>
</tr>
</tbody>
</table>

AIC 5464.5 5455.8 5434.1 5435.9

Note. * $p < .10$, ** $p < .05$, *** $p < .01$.

Regarding cheating and decision time differences between males and females, a similar pattern as in Experiment 1a was observed. In Model 2, when cheating (i.e., the number of clicks outside the current browser tab) was not included as a predictor, it appeared that males made slower decisions than females. But when adding cheating as a predictor (Model 3), this effect disappeared. Instead, cheating now predicted decision times. This finding suggested, like in Experiment 1a, that males made slower decisions.
on average because they were more prone to engage in cheating, i.e., to search for the correct response online while working on the decision task. Neither numeracy, mindsets, the incentive, nor their interaction affected decision times. Hence, there was no evidence for increased effort (as indicated by decision times) for high incentives when compared to low incentives. These findings contradicted the hypotheses H4, indicating that the variation of low versus high incentives did not influence the effort decision makers invested in the decision task. Furthermore, the hypotheses H6, H9, and H11 were not supported, since there were no mindset effects or interactions of the deliberative and implemental mindsets with low versus high financial incentives.

Cheating. As a proxy for cheating behavior, the number of clicks outside the current browser tab was also analyzed as a dependent variable. The full model comparison, following the hierarchical proportional odds logistic regression procedure described above, is presented in Table 9. Model 2 turned out to be the best fitting model. Consistent with the findings from Experiment 1a, age and sex determined cheating behavior. An increase of one year was associated with reduced cheating by roughly 4% (OR = 0.96). The odds for males to cheat more were 2.45 times the odds for females. As noted above, increased cheating for males could explain why males also responded more slowly in the decision task.

Neither the incentives nor the interaction of mindsets and incentives predicted the amount of cheating in the decision task. However, there was a marginally significant effect of the implemental mindset to reduce cheating. That is, across both high and low incentives, the odds for more cheating when in an implemental mindset were 0.49 times the odds for cheating in the control condition. This was consistent with the finding from Experiment 1a, that the implemental mindset reduced cheating when incentives were contingent on performance in the task at hand (but actually increased cheating when the payment was a fixed rate). Hence, this finding replicated the effect of the implemental mindset to attenuate cheating when payment was based on performance and it indicated that this attenuating effect was not different between high and low incentives.
### Table 9

*Results of the proportional odds logistic regression on the sum of clicks outside the current browser tab during the decision task (Experiment 1b).*

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b$</td>
<td>Odds ratio</td>
<td>$b$</td>
<td>Odds ratio</td>
<td>$b$</td>
<td>Odds ratio</td>
</tr>
<tr>
<td></td>
<td>(SE)</td>
<td>[.95 CI]</td>
<td>(SE)</td>
<td>[.95 CI]</td>
<td>(SE)</td>
<td>[.95 CI]</td>
</tr>
<tr>
<td>Deliberative</td>
<td>-0.179</td>
<td>0.84 [0.48, 1.45]</td>
<td>-0.335</td>
<td>0.72 [0.40, 1.27]</td>
<td>-0.152</td>
<td>0.86 [0.40, 1.45]</td>
</tr>
<tr>
<td>(0.281)</td>
<td></td>
<td></td>
<td>(0.291)</td>
<td></td>
<td>(0.390)</td>
<td></td>
</tr>
<tr>
<td>Implemental</td>
<td>-0.345</td>
<td>0.71 [0.41, 1.21]</td>
<td>-0.453</td>
<td>0.64 [0.36, 1.11]</td>
<td>-0.706*</td>
<td>0.49 [0.22, 1.09]</td>
</tr>
<tr>
<td>(0.275)</td>
<td></td>
<td></td>
<td>(0.284)</td>
<td></td>
<td>(0.404)</td>
<td></td>
</tr>
<tr>
<td>Incentive (low)</td>
<td>-0.022</td>
<td>0.98 [0.63, 1.52]</td>
<td>0.056</td>
<td>1.06 [0.67, 1.67]</td>
<td>0.018</td>
<td>1.02 [0.45, 2.30]</td>
</tr>
<tr>
<td>(0.226)</td>
<td></td>
<td></td>
<td>(0.233)</td>
<td></td>
<td>(0.417)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.044***</td>
<td>0.96 [0.94, 0.98]</td>
<td></td>
<td></td>
<td>0.044***</td>
<td>0.96 [0.94, 0.98]</td>
</tr>
<tr>
<td>(0.011)</td>
<td></td>
<td></td>
<td>(0.011)</td>
<td></td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Sex (male)</td>
<td>0.895***</td>
<td>2.45 [1.52, 3.94]</td>
<td>2.45</td>
<td>0.940***</td>
<td>2.56 [1.58, 4.14]</td>
<td></td>
</tr>
<tr>
<td>(0.243)</td>
<td></td>
<td></td>
<td>(0.246)</td>
<td></td>
<td>(1.58)</td>
<td></td>
</tr>
<tr>
<td>Incentive $\times$ Deliberative</td>
<td>-0.415</td>
<td>0.66 [0.21, 2.09]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.588)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incentive $\times$ Implemental</td>
<td>0.480</td>
<td>1.75 [0.56, 5.44]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.570)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
</tbody>
</table>

AIC 912.8 883.0 884.6

*Note.* *p < .10, **p < .05, ***p < .01; intercepts dropped for enhanced readability.

### Discussion

Experiment 1b yielded three important insights. First, the hypothesis H3 that high financial incentives, compared with low incentives, would increase performance in an economic decision task was not supported by the data. There was no evidence for a direct effect of higher incentives on economic performance, nor was there evidence for increased effort invested in the task, as indicated by decision times, as predicted by H4. Hence, the hypotheses H3 and H4 were rejected.

Second, the results corroborated the findings from Experiment 1a that there were no direct effects of the deliberative and implemental mindsets on performance in the decision task or decision times. This means that the hypotheses H5, H6, H8, and H9 may
be rejected with some confidence. In addition, there were no significant interactions of mindsets and incentives in this experiment, H11 was also rejected. But since there was initial evidence for such interactions in Experiment 1a, this finding further highlighted that for the study of incentive effects on economic performance, incentive salience might be the more potent predictor, rather than the absolute amount of financial incentives (see also Cerasoli et al., 2014).

Third, Experiment 1b further corroborated the finding that the implemental mindset may reduce cheating behavior if performance-based incentives are provided in economic decision tasks. This finding was consistent with corresponding results from Experiment 1a and could have important implications for the discussion about the effects of motivation and volition on economic decisions. Moreover, these findings inform the debate about motivational and volitional processes in predicting honesty in economic contexts, as well as fairness and prosocial behavior more generally (e.g., Bereby-Meyer & Shalvi, 2015; Fehr & Fischbacher, 2003).

The nature of the incentive scheme in Experiment 1b could be considered as a limitation of this study. The distinction between low and high performance-based incentives was defined by the amount of money decision makers received for each correct response in the task. It could be argued that participants did not actually view the high incentive as more attractive than the low one. The high incentive (£0.20 per correct response) was four times as high as the low incentive (£0.05 per correct response). Still, the absolute amount may simply not be high enough to elicit the same processes and decisions that are instigated by real-life high incentives, e.g., the salary increase associated with a promotion to a higher management position. However, two aspects can be raised that speak against this limitation. First, the manipulation check for the incentive conditions was significant. It indicated that participants in Experiment 1b valued the high incentive higher than the low incentive. It was more important to them to increase their payment by providing correct responses when the incentive was high. Second, prior research has often used halved amounts to operationalize lower incentives (e.g., Achtziger & Alós-Ferrer, 2014). Hence, offering rewards in the high incentive condition that are four times the amount of the reference low incentive condition seemed appropriate in principle. Further research might consider more variation in the absolute amount of varied incentive conditions to corroborate the findings of Experiment 1b.
General Discussion

Two experiments with a combined sample size of $N = 626$ examined the assumption that offering financial incentives would increase performance in economic decision tasks, a conventional wisdom and well-established finding in experimental economics. A secondary aim of these studies was to explore the possibility of interactive effects of financial incentives with the deliberative and implemental mindsets. The findings indicated mixed results regarding the first aim. Performance-based financial incentives were potent predictors of economic performance when they were contrasted with a fixed rate payment (Experiment 1a). However, when comparing high and low performance-based incentives, this difference did not seem to be predictive of economic performance. Taken together, the findings thus corroborate the notion that incentive salience matters most (Cerasoli et al., 2014), i.e., the degree to which rewards are directly tied to performance, while there seems to be little evidence for the assumed linearity of incentive effects on effort and performance when increasing the absolute amount of the incentive.

This observation has important implications for the use of financial incentives as interventions targeted at promoting desired behavior, e.g., in the workplace, in health settings, or in regulating deviant behavior. The results of Experiments 1a and 1b suggest that increasing the absolute amount of rewards offered for a given target behavior may actually not affect its likelihood of occurrence (see also Cerasoli et al., 2014). Rather than increasing the absolute amount, it may seem more effective to modulate the salience of the reward, i.e., the degree to which it is directly linked to the desired behavior in question. In the case of regulating deviant behavior, for instance, this implies that closely relating punishment to deviance might in fact be more effective in reducing such behaviors than just increasing punishments (e.g., increasing fines). More salience could be achieved, for instance, by reducing the temporal gap between the deviant behavior and the punishment.

This may be true analogously for a number of other applications. Consider, for instance, tax incentives introduced to stimulate consumer spending. Rather than increasing the absolute amount of such incentives, it could prove more effective to reduce
the bureaucratic barriers for claiming them, thus making the tax incentive more directly available (i.e., salient) to individual consumers. In conclusion, if the absolute amount of rewards and punishments indeed mattered less than their salience, this could greatly enhance the cost-effectiveness of incentive schemes. Certainly, however, increasing rewards will sometimes lead to improved performance. This relation seems to hold, in particular, in the context of workplace pay for performance (e.g., Gerhart & Fang, 2015). Yet, it seems promising to further identify the circumstances under which salience may matter more than the absolute amount of the incentive, particularly when one considers the immense potential for cost containments in a variety of settings in which financial incentives are used to stimulate certain target behaviors.

Regarding mindset effects on economic performance, the picture seems rather complex. While there was no evidence in both studies for direct effects of the deliberative and implemental mindsets on economic performance, some initial evidence exists that points to the possibility of their interaction with financial incentives. In more detail, Experiment 1a revealed that the beneficial effects of the deliberative mindset on economic performance may rely on appropriate incentivization. In line with the assumption that a deliberative mindset may improve performance only when the task at hand is desirable (e.g., attractive in terms of monetary rewards), deliberative decision makers performed better in the CRT (but not in the probability judgment task) than the implemental mindset and control groups only in the performance-based incentive condition. Yet, there was no effect of the deliberative mindset on performance in Experiment 1b, in which all decision makers were offered attractive rewards based on their performance in the decision task. Future research should seek to replicate this interactive effect of the deliberative mindset and performance-based incentives (compared with fixed rate payment) to enhance the confidence in this finding.

The present experiments examined mindset effects and their interactions with incentives in a cognitively demanding economic decision task in which difficulty was held relatively constant across trials. That is, Experiments 1a and 1b manipulated task desirability by varying the nature of the financial incentive, while holding task feasibility (difficulty) relatively constant. Also, no feedback was provided until the decision task was completed. There is ample room for further investigations of mindset effects on economic performance when desirability is varied in a different way, when it is held
constant under a feasibility manipulation, when the task poses different demands on the decision maker, or when continuous feedback is provided during the task.

For instance, instead of varying the task desirability by providing different forms of incentives, task desirability could be manipulated in terms of the experienced affect or by making the task more interesting (or more fun) to work on. The task desirability is certainly determined by many more aspects than just the expected reward. Importantly, these different drivers of task desirability, as they presumably have an impact on intrinsic motivation, might interact with incentives and the deliberative and implemental mindsets in determining performance. Further research might consider this idea and test whether the hypothesized patterns of incentive effects and interactions between incentive and mindset can be observed in decision tasks that differ on these dimensions of desirability.

Task feasibility might also affect how the deliberative and implemental mindsets relate to economic performance. Since the evaluation of feasibility differs between the deliberative mindset (impartial and realistic) and implemental mindset (optimistically biased), a manipulation of task difficulty could interact with mindsets. For instance, the illusorily optimistic success expectancies that characterize the implemental mindset might affect choices and decision processes in a way that performance is impaired relative to deliberative decision makers, particularly in very easy or very difficult decision tasks (i.e., when achievement motivation is rather low; Atkinson, 1957).

Furthermore, the decision tasks used in Experiments 1a and 1b were cognitively demanding. Other types of decision tasks, for instance physical endurance tasks, may profit to a greater extent from increased persistence or effort. In particular, supporting volitional processes may promote performance in such tasks (Wolff, Bieleke, & Schüler, 2019). Hence, there may be relevant mindset effects on task performance contingent on task difficulty or the specific demands of the task at hand. Future research might address these issues by investigating mindset effects in different tasks, e.g., with varying levels of difficulty or by comparing cognitively and physically demanding tasks.

On a side note, the present experiments contribute to a large and growing body of research on the CRT by developing and validating a new four-item version of the test. These new items were based on the original ones but differed sufficiently so that the correct responses could not be found online. Given that the original items are already well
known in the general population, and the doubts this casts on its validity as a measure of cognitive reflection (Haigh, 2016), it seemed vital to foster the further development of the scale. The present research added to these recent efforts of expanding the CRT (Primi et al., 2016; Thomson & Oppenheimer, 2016; Toplak et al., 2014). Two additional findings should be mentioned with regard to the CRT. First, CRT performance was determined by the interaction of the deliberative mindset and (performance-based vs. fixed rate) incentives in Experiment 1a, although this effect was not statistically significant. This finding nevertheless emphasized that performance in the CRT may be modulated by motivational processes. More highly powered research is required to test this idea.

Second, Experiment 1b revealed that CRT performance differences for males and females could not entirely be attributed to gender differences in subjective numeracy, as was suggested by prior research (Zhang et al., 2016). Even when controlling for individual differences in numeracy, males still performed better in the CRT than females. Hence, the test appeared to capture gender differences in the propensity to rely on intuitive responses beyond what may be explained by individual differences in numerical abilities. Interestingly, there were no performance differences between males and females in the probability judgment task, which also relied on numerical ability (however, to a much lesser extent).

Another avenue for future research was hinted at by the interaction of the implemental mindset and financial incentives on cheating behavior. In the present experiments, more clicks outside the current browser tab indicated increased cheating in order to find the correct responses online. Experiment 1a revealed that decision makers in an implemental mindset were more prone to engage in cheating than control or deliberative participants when they were compensated with a fixed rate payment. That is, when their performance in the task had no consequences in terms of earnings, cheating was increased in the implemental mindset. But if performance-based payment was offered, the implemental mindset was associated with a reduction of cheating behavior, relative to the control condition and deliberative mindset. More research is required to better understand the circumstances under which being in an implemental mindset may increase or decrease an individual’s propensity to engage in cheating behavior. Again, future research should seek a replication of this novel finding and consolidate the
evidence by exploring how the implemental mindset relates to dishonest or antisocial behavior in different tasks.
CHAPTER 6

MINDSET EFFECTS ON DECISION PROCESSES UNDER RISK

This chapter reports an experiment designed to examine the effects of the deliberative and implemental mindsets on decision processes under risk. Decisions under risk are widely regarded as prototypical economic decisions. A common paradigm to investigate choices and cognitive processes in decisions under risk is the lottery choice paradigm. The lottery choice (or risky choice) paradigm has been used extensively in prior research, for instance, to demonstrate choice regularities that are inconsistent with expected utility theory (e.g., Kahneman & Tversky, 1979) or to facilitate a test of competing theories of decisions under risk (e.g., Glöckner & Herbold, 2011; Lopes & Oden, 1999; Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013). Hence, it is a well-established experimental paradigm that has been deployed in a host of empirical studies in decision research.

A central challenge of the intended investigation of motivation and volition in decisions under risk regarded the question of how to track their effects on the level of decision processes. Economic decisions often rely on automatic decision processes (e.g., Achtziger & Alós-Ferrer, 2014; Bateman et al., 2007). Hence, the aim of the present research required a method that facilitated to capture automatic processes of decisions under risk. Eye tracking, i.e., the measurement of eye movements, and pupillometry, i.e., measuring the changes in pupil size over time, afforded precisely this. Eye movement and

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5 Note that large portions of this chapter were published in: Ludwig, J., Jaudas, A., and Achtziger, A. (2020). The role of motivation and volition in economic decisions: Evidence from eye movements and pupillometry. Journal of Behavioral Decision Making, 33(2), 180-195. https://doi.org/10.1002/bdm.2152. Of course, the description of the experimental procedures, reporting of the results, and the conclusions drawn from the experiment follow very closely the respective sections in the published article.
pupil dilation measurement in the lottery choice paradigm seemed particularly promising because these methods could provide insights into the function of visual attention and its downstream effects on choices (see also Orquin & Mueller Loose, 2013). As mentioned earlier, the efforts to foster our understanding of visual attention in decision making have spearheaded recent theoretical advancements in decision research in general, and in decisions under risk particularly (e.g., E. Brandstätter & Körner, 2014; Fiedler & Glöckner, 2012; Krajbich & Rangel, 2011; Stewart, Hermens, & Matthews, 2016).

The pupillometric analyses presented an additional promising opportunity to find out more about decision processes under risk. Previous research revealed that, under certain conditions, pupil sizes were indicators of both cognitive effort and affective arousal (e.g., Cavanagh, Wiecki, Kochar, & Frank, 2014; Kahneman & Beatty, 1966; Kinner et al., 2017; Urai, Braun, & Donner, 2017). With regard to risky choices, there is initial evidence for the notion that pupil size reflects arousal rather than effort. This is based on two observations. First, Fiedler and Glöckner (2012) reported that pupils dilated as a function of the lotteries’ mean expected value, i.e., lotteries with higher expected values (typically, those with higher gains) led to greater changes in pupil dilation over time. Second, Urai et al. (2017) found that pupil sizes traced different levels of decision uncertainty. Both higher expected values (desirability) and increased uncertainty in decision making were presumably associated with higher levels of affective arousal.

The earlier work on the lottery choice paradigm includes the investigation of incentive effects on risky choices (e.g., Beattie & Loomes, 1997; Wilcox, 1993), the analysis of attentional processes in risky choices (e.g., E. Brandstätter & Körner, 2014; Fiedler & Glöckner, 2012; Stewart et al., 2016), and an exploration of mindset effects in risky choices (Rahn et al., 2016b). However, there is no study, so far, which combines these three aspects, that is, incentivization, process tracing, and the experimental manipulation of motivation and volition (i.e., the deliberative and implemental mindsets). The present experiment addresses this gap, providing the first examination of mindset effects on risky choices, and their underlying decision processes, in an incentivized lottery choice task.

Experiment 2 was based on a version of the lottery choice task which contained 40 individual lottery choices originally developed to facilitate the comparison of
competing theories of decisions under risk (Glöckner & Betsch, 2008a, 2008b; Glöckner & Herbold, 2011). Hence, a well-established version of the paradigm was used. As mentioned earlier, the main objective of this experiment was the examination of deliberative and implemental mindset effects on decision processes under risk, facilitating a test of the open-mindedness and cognitive tuning hypotheses formulated above, H7 and H10, respectively (see Chapter 4: Overview of the Empirical Work). Of course, the experimental design also facilitated a test of the related hypotheses about mindsets which were already scrutinized in Experiments 1a and 1b. Specifically, the hypotheses H6 and H9 about the effects of the deliberative and implemental mindsets on decision times could be tested again, using a different economic decision task than in the previous experiments. Finally, the experiment further facilitated an additional test of the hypotheses H5 and H7 about mindset effects on economic performance and it afforded several exploratory analyses, e.g., on the contributions of cognitive effort and affective arousal in determining pupil size changes over time.

The remainder of this chapter is organized as follows. First, I will describe the methods of Experiment 2 in more detail, i.e., the experimental design, procedure, and the lottery choice task. Subsequently, I will present the results of the analyses of decision times, lottery choices, eye movements, and pupil dilations, and explain how these variables relate to the deliberative and implemental mindsets. Finally, a discussion concludes this chapter, summarizing the results and the conclusions drawn from the analyses, and following up on some ideas for further empirical inquiry that arise from this experiment.
Experiment 2

Method

Participants and design. For this study, one hundred and three participants were recruited at the Zeppelin University’s ZF Campus. The experiment was conducted at the Hugo-Eckener-Laboratory. Due to technical issues with eye tracking device, several participants had to be excluded from the analysis. That is, six participants were excluded due to randomly occurring software and hardware errors, two participants indicated prior knowledge of the experimental materials, and two participants failed to comply with the instructions (i.e., they did not work on the tasks properly as instructed). Thus, the analyses reported hereafter are based on a sample size of $N = 93$ ($n = 31$ in each condition; 48 females; age: 18 to 33 years, $M = 22.3$, $SD = 2.38$).

The experiment followed a 3 (mindset, between: control vs. deliberative vs. implemental mindset) $\times$ 5 (decision difficulty, within: very easy [I] vs. easy [II] vs. medium [III] vs. difficult [IV] vs. very difficult [V]) design. Table 10 shows the lottery choice tasks’ key features and levels of decision difficulty per type of lottery (see Appendix B for a full list of the 40 lotteries used in this study). Participants were randomly assigned to one of the mindset conditions (control vs. deliberative vs. implemental). The dependent variables were decision times, choices, fixations, and pupil dilations. Each participant made 40 lottery choices (eight per lottery type). Hence, the analyses were based on 1240 decisions per mindset condition, and 3720 decisions in total.

As compensation for their participation, all participants received a fixed show-up fee of €3. In addition to this faxed rate payment, participants received a bonus payment contingent on their choices in the lottery task. That is, the computer actually played the lotteries based on the participants’ choices and added up the individual yield of lottery wins. This individual performance-based financial incentive ranged between €5.37 and €16.37 ($M = 8.46$, $SD = 2.19$). Incentives did not differ across conditions or gender ($Fs \leq .162$).
Table 10
Lottery types, decision difficulty, and key features of the lottery choice task in Experiment 2. Lottery types and the definition of key features are based on Glöckner and Herbold (2011).

<table>
<thead>
<tr>
<th>Lottery type</th>
<th>Decision difficulty</th>
<th>Key features</th>
</tr>
</thead>
<tbody>
<tr>
<td>CERT(pro)</td>
<td>I</td>
<td>One zero outcome for B; certainty effect points to A</td>
</tr>
<tr>
<td>MED(alm Cert)</td>
<td>II</td>
<td>A medium outcome is almost certain for B</td>
</tr>
<tr>
<td>MED(cert)</td>
<td>III</td>
<td>A medium outcome is certain A</td>
</tr>
<tr>
<td>CERT(con)</td>
<td>IV</td>
<td>One zero outcome for A; certainty effect points to B</td>
</tr>
<tr>
<td>SIM</td>
<td>V</td>
<td>High similarity of all outcomes</td>
</tr>
</tbody>
</table>

Procedure and materials. Participants were invited for individual sessions to the laboratory. Hard contact lenses and eye make-up impaired the eye tracking measurement, so participants were asked to remove eye make-up and visual aids if necessary. Participants were screened out if they had prior experience with similar research (two participants). Detailed instructions for the lottery choice task and the incentive scheme were provided before participants signed an informed consent sheet. Participants were then familiarized with the eye tracking equipment. The eye tracking device used in this study was a desk-mounted monocular SMI iView XTM Hi-Speed operating at 240 Hz sampling frequency. For all participants, the eye tracker was set up to track the movements and pupil dilations of the right eye. No participant indicated that the left eye would be their dominant one.

Experimental manipulation. Before participants worked on the lottery choice task, a paper-and-pencil questionnaire was administered to induce either a deliberative or implemental mindset. The mindset induction procedure was very similar to that used in Experiments 1a and 1b. It was based on a procedure developed by Gollwitzer and Kinney (1989; see also Hügelschäfer & Achtziger, 2014). Participants in the deliberative mindset condition thought about an unresolved personal concern of their own choosing. They were asked to think of a personal problem that they were pondering about for some time but were undecided whether to take action on it or not (e.g., “Should I look for a new
A detailed example was provided before participants proceeded to describe several positive and negative immediate and long-term consequences of acting and non-acting on their concern. Subsequently, they rated for each indicated consequence how important it was to them and how likely they thought it would occur. This task ensured that participants carefully weighed the pros and cons of different choice options related to a personally relevant concern and thereby adopted a deliberative mindset.

In the implemental mindset condition, participants were asked to specify a personal project they were already committed to (i.e., they had already decided to pursue it) but had not yet taken any action on achieving it (e.g., “I want to apply for a scholarship!”). Again, a detailed example was presented before participants proceeded to list up to seven specific steps of action that would be required to bring them closer to their goal. They indicated for each action step, when, where, and how they intended to act. This procedure ensured that participants engaged in the diligent planning of goal-directed action associated with a personally relevant issue, thereby adopting an implemental mindset to support this process. In both conditions, it took the participants between 20 and 40 minutes to complete the mindset induction procedures. There was no time limit set for this task.

In the control condition, participants proceeded immediately to the lottery choice task after signing the consent sheet. Note that no neutral (control) mindset was used in this experiment. In some earlier mindset studies, participants in the control condition were induced with a neutral mindset to account for the potentially confounding effects of time and workload fatigue induced by the deliberative and implemental mindset induction procedures. That is, the increased workload of processing the mindset induction procedures prior to the main experimental task could produce unintentional effects on the measurement of the dependent variables. A neutral mindset induction, then, mirrored the workload and time of the deliberative and implemental mindset tasks before measuring the dependent variables, while not triggering the cognitive procedures that are activated by the deliberative and implemental mindset inductions. To control for the potentially confounding effects of time and workload in this way, earlier studies have asked participants to work on a simple, generic task before proceeding to the main experimental task. For instance, E. Harmon-Jones and Harmon-Jones (2002) had participants in this neutral mindset (control) condition report on everyday activities. Participants in Keller
and Gollwitzer’s (2017) neutral mindset condition counted the appearances of the letter “m” in a prose text written in a foreign language.

However, previous work showed that the carry-over effects of the deliberative and implemental mindsets as elicited by the induction procedures described above could not be reduced to the increased workload or merely the time that passed when processing these tasks. Harmon-Jones and Harmon-Jones (2002) showed that the deliberative and implemental mindsets, compared with a neutral mindset, produced distinct effects on post-decisional attitudes and negative affect. The implemental mindset was associated with comparatively greater reduction of cognitive dissonance. Relative to the neutral mindset, both the deliberative and implemental mindsets tended to increase negative affect. Also, Keller and Gollwitzer (2017) showed that the deliberative and implemental mindsets affected risk perception and risk-taking behavior differently than a neutral mindset. In this study, implemental participants estimated their own risk of incurring negative future life events as being lower than did participants in the deliberative or neutral mindset. On the other hand, participants in the deliberative mindset showed less risk taking in the balloon analogue risk task (Lejuez et al., 2003) compared to implemental or neutral participants. Hence, the deliberative and implemental mindset inductions influenced cognitive processes in the subsequent task beyond the mere effects of time and workload fatigue. Time and fatigue effects should have emerged in the neutral mindset condition alike, because this task was equally demanding and it took about the same amount of time to complete it.

Further support for the argument that effects of time and workload fatigue are negligible comes from a recent study in which both a neutral mindset and a baseline control condition (i.e., no additional neutral mindset task prior to the main experimental task) were included (Li et al., 2019). In this study, it was discovered that decision task performance, i.e., decision times and error rates, did not differ between the neutral mindset and the baseline control conditions, but were affected by the deliberative and implemental mindsets. Hence, mindset effects were qualitatively different from both the neutral mindset and the baseline condition. But the latter two did not produce different outcomes. Based on this evidence, I argue that mindset effects as typically observed based on the induction procedure used in this study are not based on workload-induced fatigue.
or merely the time that expired between the mindset induction and measurement of the dependent variables.

**Lottery choice task.** As mentioned earlier, the lottery choice task was adapted from a previous experiment by Glöckner and Herbold (2011). It contained 40 lotteries, each consisting of two gambles with equal (or close to the same) expected values. An example lottery is presented in Figure 4. Each gamble contained two possible outcomes and their respective probabilities $p$ and $1 - p$, i.e., probabilities always added up to 1 within gambles. Participants indicated their preference for one of the two gambles (Gamble A displayed on the left, Gamble B on the right) by pressing the left or right button of a response pad (Cedrus RB-530) that was located on the table in front of them, between the eye tracker and the computer monitor. Participants had their hands placed on the response pad for the whole duration of the decision task, so that looking at the response buttons was not required.

![Example of the lottery choice task with two gambles](image)

This particular lottery choice task was originally developed to facilitate a test of competing theories of decisions under risk, i.e., compensatory versus non-compensatory choice models (see Glöckner & Herbold, 2011). The present experiment did not scrutinize these theories but examined the role of motivation and volition in determining economic decisions and the cognitive processes that underlie them. In doing so, the lottery choice task as developed by Glöckner and Herbold (2011) was used, but the five types of lotteries were re-arranged on a dimension of task difficulty, as proposed by Rahn et al. (2016b). Empirical mean decision times observed for the categories of the task determined the level of difficulty. That is, lotteries with longer decision times were categorized as difficult decisions, while lotteries with faster decision times were categorized as easy decisions (see also Schotter, Berry, McKenzie, & Rayner, 2010). The lottery types and the decision times observed in the present experiment, as well as the previous research mentioned above, are shown in Table 11.

Table 11
Comparison of decision times (in seconds) per decision difficulty in three studies.

<table>
<thead>
<tr>
<th>Decision difficulty</th>
<th>GH</th>
<th>RJA</th>
<th>Present study</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>8.4 (.30)</td>
<td>8.7 (.37)</td>
<td>9.0 (.57)</td>
</tr>
<tr>
<td>II</td>
<td>8.6 (.30)</td>
<td>9.1 (.38)</td>
<td>9.9 (.72)</td>
</tr>
<tr>
<td>III</td>
<td>8.8 (.30)</td>
<td>9.5 (.39)</td>
<td>10.9 (.39)</td>
</tr>
<tr>
<td>IV</td>
<td>9.7 (.31)</td>
<td>10.0 (.41)</td>
<td>10.2 (.75)</td>
</tr>
<tr>
<td>V</td>
<td>11.8 (.31)</td>
<td>10.7 (.46)</td>
<td>12.5 (.86)</td>
</tr>
</tbody>
</table>

The lotteries were presented on a monitor set up at 700 mm distance from the participants’ eyes (AOC LM927U LCD-monitor, resolution 1280 × 1024 pixels, refresh rate 60 Hz). The order in which the 40 lotteries were presented was fully randomized using Presentation 17.1 (Neurobehavioral Systems, Albany, CA, USA). The program recorded decision times and choice data (left or right button press). Each lottery was preceded by a blank screen (2000 ms) and fixation cross (1000 ms) and remained on-screen until the participants responded.

Compared with the presentation format used in Glöckner and Herbold (2011), Rahn et al. (2016b), and other recent eye tracking studies of decisions under risk (e.g., Fiedler & Glöckner, 2012), some minor changes were introduced to the on-screen appearance of the lotteries. This was done to accommodate recent criticism of the paradigm (E. Brandstätter & Körner, 2014). Specifically, the on-screen design of the lotteries was changed so that all pieces of information (a) had the same distance to the center of the screen; (b) were framed and presented in white font on black background to impede peripheral perception of larger versus smaller arrays; and (c) were fully randomized regarding their on-screen position to avoid habituation and sequence effects, as well as effects of reading direction or central gaze bias. Eight non-overlapping areas of interest (AOIs) were defined around the eight pieces of information displayed on the screen, i.e., the four lottery outcomes and their four probabilities (179 x 105 pixels per AOI). The eye movement and pupil dilation raw data (i.e., one sample roughly every 4 ms) were recorded using the SMI iViewX 2.2 software package (SensoMotoric Instruments, Teltow, Germany). The appropriate adjustment of the eye tracker was assured by a 2-step 9-point device-controlled calibration procedure.

**Incentive and further measures.** Participants’ payment depended on their choices in the lottery task. Each chosen gamble was actually played by the computer and participants were informed that each outcome would add up to their individual yield of experimental currency units (E). An exchange factor of 580 was previously determined to ensure an average earning of around €11 for each participant (i.e., E580 won in the task were equal to a payment of €1). After completion of all lottery choices, a full list of gamble outcomes and the total sum of earnings in E and € was presented. During the task, the participants did not receive any feedback on the outcome of their lottery choices.
When participants had completed the lottery choice task, they were asked to work on a web-questionnaire on demographic questions and manipulation check items. The post-experimental questionnaire was implemented using SoSciSurvey (www.soscisurvey.de, Munich, Germany) and contained the following measures. Building on prior work (V. Brandstätter & Frank, 2002), the quality of the deliberative and implemental mindset induction was assessed by means of self-reports, each indicated on 9-point Likert scales, of clarity of instructions (1 item), effort in task completion (1 item), amount of thinking about the personal concern (1 item), commitment to the personal concern (2 items), and determination to act according the personal concern (2 items). Additional self-report measures included a scale for general achievement motivation (AMS-R-10: ten items, 4-point Likert scale; Lang & Fries, 2006) and general self-efficacy (ASKU: three items, 5-point Likert scale; Beierlein, Kovaleva, Kemper, & Rammstedt, 2012). Participants also evaluated the lottery choice task in terms of the clarity of instructions (1 item), overall difficulty (1 item), feasibility (1 item), desirability of the task (2 items), and the subjective valence of the financial incentive (3 items). Again, a 9-point Likert scale was used for these items. Finally, the participants were debriefed, thanked, and paid according to their individual earnings in the lottery choice task.

**Manipulation check**

The manipulation checks indicated that the induction of the deliberative and implemental mindsets was successful. As measures of reliability, the Spearman-Brown coefficient $\rho$ is reported for two-item scales and Cronbach’s $\alpha$ for scales including three or more items. As expected, participants in the deliberative mindset reported having had more thoughts about their personal concern or project than implemental participants ($M_{\text{del}} = 7.00$, $SD = 0.97$; $M_{\text{imp}} = 6.32$, $SD = 1.58$), $t(60) = 2.04$, $p = .046$, $d = 0.519$. This was likely due to the deliberative mindset induction task’s demand to thoroughly weigh the pros and cons of acting versus not acting and showed that the deliberative mindset task indeed triggered more deliberation than the implemental mindset task. No difference between females and males was observed regarding the amount of thinking about personal concerns, $t(60) = 1.50$, $p = .139$.

Individuals in the implemental mindset, compared to the deliberative, scored higher on both commitment ($\rho = .69$; $M_{\text{del}} = 5.95$, $SD = 2.01$; $M_{\text{imp}} = 7.58$, $SD = 1.57$) and
determination ($\rho = .64; M_{\text{del}} = 6.03, SD = 1.70; M_{\text{imp}} = 7.53, SD = 1.09), t(60) = 3.56, p = .001, d = 0.904, and t(51.19) = 17.02, p < .001, d = 1.05, respectively. With regard to commitment and determination collapsed across experimental conditions, females were marginally more likely to be committed to pursuing their personal goals ($M_{\text{female}} = 7.17, SD = 1.66; M_{\text{male}} = 6.33, SD = 2.20), t(60) = 1.70, p = .094, d = 0.433, while females and males were equally determined to take action ($t < 1$).

Regarding the mindset tasks’ clarity of instructions, females rated the instructions more easily comprehensible than males ($M_{\text{female}} = 8.28, SD = 0.92; M_{\text{male}} = 7.60, SD = 1.45), t(48.63) = 4.78, p = .034, d = 0.564. No difference between mindsets was observed, t(51.43) = 1.26, p = .267. Females also self-reported higher effort in task completion than males ($M_{\text{female}} = 7.94, SD = 0.88; M_{\text{male}} = 7.33, SD = 1.27), t(60) = 2.19, p = .032, d = 0.562. Mindsets did not affect effort in the task, t(53.98) = 1.30, p = .260.

Regarding the lottery choice task, no effects of mindset or gender were observed on the clarity of instructions ($F$s < 1). Task difficulty and feasibility were assessed equally across mindsets and sex (all $F$s ≤ 2.06, $ps ≥ .133). Males reported higher desirability of the lottery choice task than females ($\rho = .82; M_{\text{female}} = 6.50, SD = 1.34; M_{\text{male}} = 7.06, SD = 1.41), F(1, 87) = 4.65, p = .034, $\eta^2 = .051. Mindsets did not affect task desirability ($F < 1$), no interaction of mindset and sex was observed. Finally, the self-reported valence of the financial incentive ($\alpha = .77$) was not affected by mindset, sex, or their interaction (all $F$s ≤ 1.99, all $ps ≥ .143$).

As additional measures to check the quality of the mindset inductions, the deliberative and implemental mindsets were compared on both, the Hope-of-Success ($\alpha = .75$) and Fear-of-Failure ($\alpha = .75$) subscales of the Revised Achievement Motives Scale (AMS-R-10; Lang & Fries, 2006), and with regard to general self-efficacy (ASKU, $\alpha = .65$; Beierlein et al., 2012). Three separate 3 (mindset, between: control vs. deliberative vs. implemental) $\times$ 2 (sex, between: female vs. male) analyses of variance were run to test for possible mindset effects on these measures.
Hope-of-Success was not affected by mindset or the interaction of mindset and sex ($F$s < 1), but there was a significant main effect of sex ($M_{\text{female}} = 3.29$, $SD = 0.43$; $M_{\text{male}} = 3.54$, $SD = 0.46$), $F(1, 87) = 7.35$, $p = .008$, $\eta^2 = .078$. This indicated that males had generally more optimistic expectations of success than females. Fear-of-Failure was determined by mindsets ($M_{\text{con}} = 2.30$, $SD = 0.50$; $M_{\text{del}} = 2.40$, $SD = 0.58$; $M_{\text{imp}} = 2.05$, $SD = 0.61$), $F(2, 87) = 3.26$, $p = .043$, $\eta^2 = .070$. There were no effects of sex or the interaction of mindsets and sex. The significant effect of mindset was driven by decreased Fear-of-Failure in the implemental mindset compared to the deliberative mindset and the control condition (see also Figure 5). This finding was consistent with the notion of self-serving optimism in the implemental mindset (e.g., Gollwitzer & Bayer, 1999; Taylor & Gollwitzer, 1995). It also added to more recent evidence pointing to increased achievement motivation in the implemental mindset (V. Brandstätter et al., 2015; Rahn et al., 2016b). The results from this experiment suggested that mindset effects on achievement motivation were driven by reduced Fear-of-Failure in the implemental mindset, rather than individual differences in evaluating the probability of success in future tasks (as suggested by Puca, 2005). Regarding general self-efficacy, there was only a descriptive effect of mindset in the expected direction ($M_{\text{con}} = 4.16$, $SD = 0.49$; $M_{\text{del}} = 4.14$, $SD = 0.47$; $M_{\text{imp}} = 4.37$, $SD = 0.42$; see also Figure 5), i.e., more general self-efficacy for implemental participants compared with deliberative and control. However,
the mindset effect did not reach statistical significance, $F(2, 87) = 2.22, p = .115, \eta^2 = .049$. There were no effects of sex and no interaction of mindset and sex ($Fs < 1$).

Results

Decision times. The decision times observed in the experiments by Glöckner and Herbold (2011) and Rahn et al. (2016b) determined the lotteries’ level of difficulty in the present study. Hence, the analysis of decision times should be considered a manipulation check for decision difficulty. Table 11 presents mean decision times per category of the lottery choice task in the previous work and the present experiment. Overall, decision times were slightly longer in the present experiment than in the previous research. Although rank ordering lottery types by their mean decision times resulted in a different assignment of levels of difficulty for medium (III) and difficult (IV) lotteries, it could be concluded that the decision time data, at large, resembled the results from the earlier studies. Thus, the manipulation of decision difficulty was successful. I will return to the issue of different rank order of difficulty in the Discussion section.

For the analysis of decision times dependent on difficulty and mindset, linear mixed-effect model analyses were conducted, following a step-up procedure. In doing so, a reduced baseline model was fitted at first which included only the random effects of lotteries and participants. Subsequently, the fixed effects of (a) decision difficulty, (b) mindset, and (c) their interaction were added in a stepwise fashion. To perform significance tests for the fixed effect in question, likelihood ratio tests were conducted to compare the model including the fixed effect to the last best fitting model. If the difference between the likelihood of the two compared models was significant, it was concluded that the fixed effect in question was significant. Model goodness of fit was evaluated by the Akaike Information Criterion (AIC). The difference in AICs was calculated for every step of the analytical procedure by subtracting the current step’s model AIC from the previous best fitting model’s AIC. Hence, negative values indicate a reduction of AIC for the current step, and thus, improved model fit. In addition, mixed-effects model estimates for the fixed effects and .95 confidence intervals are reported. The analyses were run in R using the `lmer` function from the package `lme4` (Bates et al., 2015; R Core Team, 2016). Note that maximum likelihood estimation was used to fit
the models, since maximum likelihood, as opposed to REML, facilitated model comparisons by and fixed effect significance testing by means of likelihood ratio tests. Except for some minor differences explained below, this general procedure was used for all the dependent variables of interest in Experiment 2.

Decision times were log-transformed prior to the analyses in order to reduce the skewness of the decision time analyses. As described, a baseline model was fitted entering only lotteries and participants as random effects. Adding the decision difficulty factor to this reduced baseline model indicated that difficulty determined decision times, $\chi^2(4) = 50.75, p < .001 \ (AIC_a - AIC_0 = -42.8)$. Adding the fixed effect of mindset revealed that mindsets tended to affect decision times, $\chi^2(2) = 5.66, p = .059 \ (AIC_b - AIC_a = -1.7)$. Based on the model in which both the fixed effects of difficulty and mindset were entered, the effect of difficulty indicated an increase of decision times with higher levels of decision difficulty (the increase of log decision time relative to very easy [I] lotteries, II: 0.06 [-0.01, 0.13], III: 0.18 [0.11, 0.25], IV: 0.09 [0.02, 0.16], V: 0.33 [0.26, 0.40]). The marginal effect of mindset was in line with the hypothesis H6, suggesting that decision times were longer in the deliberative mindset than in the control condition (an increase in log decision time of 0.22 [0.04, 0.40] for the deliberative mindset relative to control; the implemental mindset estimate was 0.08 [-0.10, 0.26]).

As a final step, the interaction of difficulty and mindset was added to the model. Comparison of the interaction model to the previous one indicated a significant interaction of difficulty and mindset, $\chi^2(8) = 17.78, p = .023 \ (AIC_c - AIC_b = -1.7)$. This interaction suggested that mindset effects on decision times differed across levels of decision difficulty. In fact, separate models computed for the five lottery types, each entering mindset as fixed effect, confirmed that mindset determined decision times in the case of very easy (I) and very difficult (V) lotteries (likelihood ratio test $ps \leq .035$). Yet, mindset only tended to determine decision times in difficult (IV) lotteries ($p = .064$) and did not affect decision times in easy (II) and medium (III) lotteries ($ps \geq .171$). Estimating models separately for the mindset conditions indicated that difficulty was a significant predictor of decision times in all conditions, all $ps < .001$. Hence, the deliberative and implemental mindsets determined decision times only in the case of rather easy and difficult decisions, but not if decisions were of medium difficulty.
**Lottery choices.** Decisions in the lottery choice task were coded as a dummy variable (1 for choice of Gamble A, 0 for Gamble B). Logistic mixed-effects model analysis was conducted to analyze how decision difficulty (five levels of difficulty: I vs. II vs. III vs. IV vs. V) and mindsets (control vs. deliberative vs. implemental) would impact decisions to choose Gamble A. The procedure followed a step-up approach. That is, a baseline model with only the random effects of lotteries and participants was computed at first. Subsequently, the fixed effects in question were added to that model: (a) the fixed effect of difficulty, (b) both fixed effects of difficulty and mindset, and (c) the fixed effects of difficulty, mindset, and their interaction. These models were then compared using likelihood ratio tests to evaluate if the added fixed effect in question was significant. As a measure of comparative model fit, the difference in AICs for the compared models is given (Burnham & Anderson, 2002). In doing so, the AIC of the last best fitting model is subtracted from the current model in question. That is, if the difference in AICs is negative, there is an increase of model fit by adding the fixed effect in question. If the value is positive, adding the fixed effect does not improve model fit. All models were fitted in R using the `glmer` function from the package `lme4` (Bates et al., 2015; R Core Team, 2016).

The first model comparison (i.e., comparing the difficulty model to the reduced baseline model including only the random effects) indicated that decision difficulty determined lottery choices, $\chi^2(4) = 92.64, \ p < .001$ (AIC$_a$ - AIC$_b$ = -84.7; estimates relative to very easy [I] lotteries: II: -1.43 [-1.76, -1.10], III: -1.16 [-1.49, -0.83], IV: -2.90 [-3.23, -2.56], V: -1.64 [-1.97, -1.31]). As a next step, the fixed of mindset was added to that model. The likelihood ratio test indicated that adding mindset did not increase the model fit, $\chi^2(2) = 1.15, \ p = .563$ (AIC$_b$ - AIC$_a$ = 2.8). Hence, the experimental manipulation of the deliberative and implemental mindsets did not influence lottery choices. Finally, a logistic mixed-effects model with difficulty, mindset, and their interaction as fixed effects was compared to the model with only difficulty as a fixed effect. The comparison indicated no interaction of decision difficulty and mindset, $\chi^2(10) = 15.38, \ p = .119$ (AIC$_c$ - AIC$_b$ = 4.6).

To enhance the comparability with prior work using the same paradigm (Glöckner & Betsch, 2008a, 2008b; Glöckner & Herbold, 2011; Rahn et al., 2016b), the choice data was aggregated across trials within each category of the decision task as the probability of choosing Gamble A. The decision difficulty effect on lottery choices, as reported by the previous studies, was replicated. Figure 6 shows that gambles including (almost) sure gains were preferred on average. However, the choice proportions for Gamble A remained close to chance (i.e., close to .5) when the gambles’ structure of outcomes and probabilities was highly similar, in the sense that the range of possible gains and their probabilities was rather narrow. The means and standard deviations of the probability of choosing Gamble A are presented in Table 12 for all lottery types (collapsed across mindset conditions, since mindsets did not affect choices).
Table 12

*Means and standard deviations (in parentheses) for the probability of choosing Gamble A, the mean number of fixations per decision, and the fraction of fixations directed at probabilities.*

<table>
<thead>
<tr>
<th>Decision difficulty</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Probability for choice A</td>
<td>.867</td>
<td>.613</td>
<td>.673</td>
<td>.272</td>
<td>.562</td>
</tr>
<tr>
<td></td>
<td>(.19)</td>
<td>(.28)</td>
<td>(.26)</td>
<td>(.24)</td>
<td>(.18)</td>
</tr>
<tr>
<td>Mean number of fixations per decision</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>30.25</td>
<td>32.63</td>
<td>35.78</td>
<td>34.78</td>
<td>41.29</td>
</tr>
<tr>
<td></td>
<td>(10.61)</td>
<td>(11.71)</td>
<td>(12.27)</td>
<td>(13.46)</td>
<td>(13.80)</td>
</tr>
<tr>
<td>Deliberative</td>
<td>36.70</td>
<td>36.96</td>
<td>40.35</td>
<td>42.90</td>
<td>51.80</td>
</tr>
<tr>
<td></td>
<td>(10.63)</td>
<td>(10.66)</td>
<td>(11.22)</td>
<td>(15.85)</td>
<td>(16.78)</td>
</tr>
<tr>
<td>Implemental</td>
<td>32.30</td>
<td>36.67</td>
<td>39.86</td>
<td>36.22</td>
<td>45.64</td>
</tr>
<tr>
<td></td>
<td>(13.82)</td>
<td>(14.85)</td>
<td>(15.21)</td>
<td>(15.47)</td>
<td>(15.86)</td>
</tr>
<tr>
<td>Fraction of fixations on probabilities</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>.487</td>
<td>.463</td>
<td>.453</td>
<td>.495</td>
<td>.462</td>
</tr>
<tr>
<td></td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.03)</td>
</tr>
<tr>
<td>Deliberative</td>
<td>.469</td>
<td>.462</td>
<td>.448</td>
<td>.471</td>
<td>.452</td>
</tr>
<tr>
<td></td>
<td>(.04)</td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.04)</td>
<td>(.04)</td>
</tr>
<tr>
<td>Implemental</td>
<td>.492</td>
<td>.472</td>
<td>.451</td>
<td>.504</td>
<td>.466</td>
</tr>
<tr>
<td></td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.03)</td>
<td>(.03)</td>
</tr>
</tbody>
</table>


**Eye tracking data quality.** In order to check the quality of the eye tracking data, the results of the control condition were compared with the results obtained in the studies by Glöckner and Herbold (2011) and Rahn et al. (2016b). These studies used the same lottery choice task, so a direct comparison and inferences about the data quality in the present study were possible. The overall mean number of fixations per decision (control condition of Experiment 2: $M = 34.95$, $SD = 11.37$, $SE = 2.04$) was very similar to the mean number of fixations in Glöckner and Herbold ($M = 36.4$, $SE = 0.83$) and Rahn et al. ($M = 40.86$, $SD = 3.78$). Table 12 shows the number of fixations per lottery type and across the three mindset conditions. Note, that the fixation count was more broadly distributed around the mean in Experiment 2 than in these previous studies.
The overall ratio of fixations that fell into one of the eight AOIs served as another indicator of data quality. It was comparable across all three studies (control condition in the present study: 86.55%, compared to 87% in Glöckner and Herbold’s and Rahn et al.’s experiments). Remember that the on-screen position of the gambles’ outcomes and probabilities was fully randomized in Experiment 2, but not in the previous studies. The similarity of the share of fixations directed at one of the AOIs highlighted that randomizing the on-screen position of gamble attributes did not affect eye tracking data quality. Overall, participants preferred the top-left quadrant (as indicated by the number of fixations), while AOIs in the bottom-right quadrant were least fixated. This pattern corresponded to the natural left-to-right, top-to-bottom reading direction in western cultures. Since all gamble attributes had the same distance to the center of the screen, no overall central fixation bias was observed (see, e.g., Clarke & Tatler, 2014).

Earlier research on eye movements in risky choices had consistently reported that the last fixation was highly predictive for choices (Fiedler & Glöckner, 2012; Glaholt & Reingold, 2009; Krajbich & Rangel, 2011; Stewart et al., 2016). That is, in most decisions, the last fixation during a risky choice was to the gamble eventually chosen by the decision maker. This was also the case in the present experiment. Overall, there was a good match of the last fixation and the chosen gamble, $M = 76.48\%$ ($SD = 9.5$). A one-way analysis of variance on the predictive power of the last fixation revealed an effect of mindset, $F(2, 90) = 3.49$, $p = .035$, $\eta^2 = .072$. Choices were better predicted by the last fixation in the deliberative mindset ($M_{del} = 79.67\%, SD = 8.4$) then in the implemental mindset ($M_{imp} = 73.47\%, SD = 7.7$), Scheffé-test $p = .035$; no other direct comparison of conditions was significant ($M_{con} = 76.29\%, SD = 11.3$), $ps \geq .361$.

Finally, the duration of the last fixation in the present experiment was also compared to earlier research to assess the quality of the eye tracking data. Note that the first fixation was excluded from this analysis, since its position and duration were likely to be biased by the preceding fixation cross (see Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; Krajbich et al., 2010). The last fixation was longer than all other (middle) fixations, $t(92) = 11.81$, $p < .001$, $d = 1.502$ ($M_{last} = 425.92$ ms; $M_{rest} = 228.22$ ms). Mindsets did not affect the mean duration of the last fixation ($F < 1$). This finding was consistent with prior eye movement data in decision research (Stewart et al., 2016), and
thus, further validated the data quality in the present experiment. It should be noted, however, that the attentional drift diffusion model (e.g., Krajbich & Rangel, 2011; S. M. Smith & Krajbich, 2019; Tavares, Perona, & Rangel, 2017) predicts that the last fixation should be shorter than all other fixations. I will return to this issue shortly in the Discussion Section.

**Information search (fixations).** The means and standard deviations for the number of fixations per decision, dependent on decision difficulty and mindset condition, are shown in Table 12. Linear mixed-effects models with random intercepts for lotteries and participants were used to analyze the number of fixations per decision. Again, likelihood ratio tests assessed the significance of the fixed effects of decision difficulty and mindset, that were added stepwise to a reduced baseline model (only random effects) in the following order: (a) difficulty, (b) both difficulty and mindset, and (c) difficulty, mindset, and their interaction. Comparative model fit was assessed by comparing the difference in AICs (see above). Again, the linear mixed-effect models were fitted in R using the function lmer from the package lme4 (Bates et al., 2015; R Core Team, 2016). Importantly, the number of fixations per decision and decision times (reported above) correlated very highly by nature. Therefore, these measures, and thus, the analyses, cannot be considered independent.

First, a baseline model (including only the random effects of lotteries and participants) was compared to a model extended by the decision difficulty factor. Difficulty determined the number of fixations per decision, as indicated by the likelihood ratio test, $\chi^2(4) = 44.28$, $p < .001$ (AIC$_a$ – AIC$_b$ = -36.3). Adding mindsets to this model indicated a tendency of mindsets to influence the number of fixations per decision, $\chi^2(2) = 4.95$, $p = .084$ (AIC$_b$ – AIC$_a$ = -1.0). Based on the model including both the effects of difficulty and mindsets, the difficulty effect indicated that more difficult lotteries were associated with higher numbers of fixations (increase in the number of fixations relative to very easy (I) lotteries: II: 2.27 [-0.76, 5.31], III: 5.52 [2.48, 8.56], IV: 4.82 [1.79, 7.86], V: 13.10 [10.06, 16.14]). The marginally significant effect mindset was consistent with the hypothesis H7, suggesting that relative to the baseline control condition, being in a deliberative mindset increased the number of fixations per decision by 6.83 [0.89, 12.79]. The implemental mindset estimate was 3.19 [-2.75, 9.14].
As a next step, the interaction of difficulty and mindset was added to the model. The interaction was significant, $\chi^2(8) = 21.10, p = .007$ (AIC$_c$ – AIC$_b$ = -5.1), suggesting that the effect of mindset on the number of fixations differed across lottery types. To decompose this interaction, separate linear mixed-effect models were computed for each lottery type. The separate analyses showed that mindsets determined the number of fixations in very difficult (V) lotteries (likelihood ratio test: $p = .029$), tended to affect fixation count in very easy (I) and difficult (IV) lotteries ($ps \leq .074$), but did not influence the number of fixations in easy (II) and medium (III) lotteries ($ps \geq .308$). Estimating separate mixed-effect models for each mindset conditions revealed that decision difficulty was a significant predictor of the number of fixations in all mindset conditions, all $ps < .001$. Hence, the interaction of difficulty and mindset was driven by the different effect of mindsets for the distinct levels of decision difficulty.

Next, I intended to test whether the deliberative and implemental mindsets would affect the attentional preference for particular information included in the gambles, i.e., either outcomes or probabilities. This was predicted by hypothesis H10, stating that information related to feasibility (probability) should be preferentially processed when in an implemental mindset. To test this hypothesis, the fraction of fixations on probabilities was computed by dividing the number of fixations on probabilities by the total number of fixations. The fraction of fixations on probabilities and the fraction of fixations on outcomes added up to 1, so this measure could, in principle, be interpreted as reflecting attentional preference for particular gamble attributes when it deviated from .50. But such interpretations of the absolute value of this measure should be considered with caution, because it might reflect familiarity rather than preferential processing (see Orquin & Holmqvist, 2018). Therefore, I limited the interpretation of this measure to comparisons across experimental conditions (i.e., decision difficulty and mindset). The means and standard deviations for the fraction of fixations on probabilities, dependent on the lottery type and mindset, are given in Table 12.

Again, linear mixed-effects model analyses with random intercepts for lotteries and participants were performed. First, I computed a baseline model (only random effects) to be compared with models that extended by the fixed effects of (a) difficulty, (b) both difficulty and mindset, and (c) difficulty, mindset, and their interaction. The first
comparison revealed that decision difficulty determined the fraction of fixations on probabilities, $\chi^2(4) = 43.90, p < .001$ (AIC$_a$ – AIC$_0$ = -35.9). Further model comparisons indicated that mindsets also influenced the fraction of fixations on probabilities, $\chi^2(2) = 8.23, p = .016$ (AIC$_b$ – AIC$_a$ = -4.2). The fixed effect estimates for difficulty, based on the model including both difficulty and mindset as fixed effects, indicated the following changes in the fraction of fixations on probabilities relative to very easy (I) lotteries: II: -.015 [-.025, -.005], III: -.033 [-.043, -.023], IV: .006 [-.003, .017], V: -.022 [-.032, -.012]). Mindsets affected the fraction of fixations on probabilities in line with the hypothesis H10. The fraction was reduced in the deliberative mindset by -.009 [-.019, .001] and increased by .007 [-.004, .017] in the implemental mindset, relative to the baseline control condition. Hence, the hypothesis that decision makers in an implemental mindset would preferentially look at feasibility-related gamble information, i.e., probabilities, was supported.

The comparison of the interaction model with the model including only difficulty and mindset as fixed effects (but not their interaction) revealed a significant interaction, $\chi^2(8) = 15.61, p = .048$ (AIC$_c$ – AIC$_b$ = 0.4). This interaction suggested that mindsets determined the fraction of fixations on probabilities differently dependent on the level of decision difficulty. To test this assumption, five separate linear mixed-effects models for each type of lottery were fitted, each including mindset as a fixed effect and participants as a random effect. The separate model analyses indicated that mindsets were a marginally significant predictor of the fraction of fixations on probabilities in very easy (I) lotteries ($p = .088$), and they determined the fraction in difficult (IV) lotteries ($p < .001$), but not in any other type of lottery ($ps \geq .171$ for II, III, and V lotteries).

An interesting observation was that the two types of lotteries, in which the fraction of fixations on probabilities was influenced by the deliberative and implemental mindsets, contained a zero-outcome in one gamble (but note that this was also true for type II). In these categories of the decision task, choices were heavily biased toward the gamble that did not include the zero-outcome (see Table 12, Figure 6, and also Glöckner & Herbold, 2011). That is, zero-outcomes appeared to drive attention to probabilities, and this effect was particularly strong for participants in an implemental mindset. Separate model estimations for each mindset condition indicated that difficulty was a significant predictor
of the fraction of fixations on probabilities in all mindset conditions, all likelihood ratio test \( ps < .001 \). This confirmed that the interaction of difficulty and mindsets in determining the fraction of fixations on probabilities was driven by different effects of mindset contingent on the type of lottery.

For further exploration of how pre-decisional information search was determined by lottery types, I next took a closer look at the distribution of attention, i.e., fixations, across the four outcomes of one lottery. Separate linear mixed-effects models were estimated for the fraction of fixations to outcomes, with lotteries and participants entered as random effects and the outcomes (A1, A2, B1, B2) as fixed effect. This analysis facilitated a test of whether a higher or lower share of the overall attention to outcomes would be deployed to particular types of outcomes (e.g., zero-outcomes). For instance, Glöckner and Herbold (2011) reported that zero-outcomes received relatively less attention in terms of fixations (see also Franco-Watkins & Johnson, 2011).

The distribution of fixations across the four outcomes of one lottery differed for all lottery types (all \( ps \leq .004 \); indicated by likelihood ratio tests against a baseline model with only the random effects). That is, in no lottery type did all four outcomes receive the same equal share of attention to outcomes. Yet, the range of how fixations to outcomes were distributed differed considerably between difficulty levels. There was roughly equal distribution of fixations across the four outcomes of one lottery for medium (III) and very difficult (V) lotteries, i.e., each outcome received close to 25% of the overall attention to outcomes as measured by the total number of fixations on outcomes (ratios ranged between .23 and .28 for lottery type III, and between .24 and .25 for lottery type V). For the remaining lottery types (I, II, IV), there were considerably greater differences in the distribution of attention across the four outcomes. Specifically, in these lotteries, one outcome was substantially less fixated than the other ones (least fixated outcomes with ratios of .19, .19, and .17, for lottery types I, II, and IV, respectively). Notably, the least fixated outcome was a zero-outcome in all lottery types. This finding was consistent with earlier research (e.g., Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011) and suggested that zero-outcomes play an important role in information search in decisions under risk. They might be disregarded in terms of visual attention to save cognitive resources that can be invested in processing more attractive outcomes with gains larger
than zero, or they could be treated similarly to losses and, perhaps in addition to the first effect, trigger motivational and affective processes rather distinct from other gamble attributes. I will return to this point in the Discussion of Experiment 2, and in fact, explore these alternative explanations for the effect of zero-outcomes in decisions under risk more thoroughly in Experiment 3.

**Pupil dilation.** Pupil dilation raw data was aggregated to facilitate the examination of how difficulty and mindsets influenced pupillary responses in the lottery choice task. Only trials were analyzed in which decision makers took at least four seconds to make their lottery choices, and only the first four seconds of every trial were analyzed. This resulted in the exclusion of 190 decisions (5.1% of all trials) with decision times < 4000 ms. Each trial was subdivided into 16 bins of 250 ms (see Cavanagh et al., 2014; Fiedler & Glöckner, 2012). For each of these bins, the mean pupil dilation in millimeters was computed based on the pupil dilation raw data. Then, the percentage of change in pupil size relative to a pre-stimulus baseline was calculated. The pre-stimulus pupil dilation baseline was determined on the level of trials, i.e., as the mean pupil dilation from 500 ms before each trial until stimulus onset. Following this procedure facilitated the examination of pupil size changes over time.

Figure 7a presents the percentage of pupil size change over time, dependent on decision difficulty. Following the step-up procedure described above, linear mixed-effects models were fitted to the pupil data, entering (a) difficulty as a fixed effect, (b) both difficulty and mindset as fixed effects, and (c) difficulty, mindset, and their interaction as fixed effects. Lotteries, participants, and bins were entered as random effects. The comparison of the difficulty model to the reduced baseline model (with only the random effects) indicated that difficulty determined the pupil size change over time, $\chi^2(4) = 19.67, p < .001$ (AIC$_a$ – AIC$_0$ = -11.7; estimates relative to very easy [I] lotteries: II: 0.47 [0.09, 0.85], III: 0.39 [0.01, 0.76], IV: 0.35 [-0.02, 0.73], V: -0.35 [-0.73, 0.03]). Visual inspection (see Figure 7a) suggested that decision difficulty influenced the pupillary response after approximately 1000 ms into the trial. That is, during the first second of decisions, pupil dilations developed similarly for each level of difficulty. But the changes in pupil size began to differ between difficulty levels from this time on. This observation can be explained by the key features of the lottery choice task’s categories
mindset effects on decision processes

Lotteries which contained extraordinarily large outcomes in absolute terms (II, III) led to greater changes in pupil dilation than lotteries with only relatively small outcomes (V). This was consistent with earlier work on pupillometry in a lottery choice task (Fiedler & Glöckner, 2012). Fiedler and Glöckner (2012, Study 2) showed that pupils dilated as a function of the lotteries’ mean expected values. The mean expected value was, of course, heavily driven by large absolute outcomes. This finding suggested that, in decisions under risk, pupil dilation may reflect the desirability of choice options rather than decision difficulty (see e.g., Kahneman & Beatty, 1966, for evidence linking pupil dilation to cognitive effort). On an important side note, lottery choices in Experiment 2 had real consequences in terms of earnings. Thus, measuring pupil dilations had some ecological validity.

Further linear mixed-effects model comparisons indicated that mindsets did not affect pupil dilation change, $\chi^2(2) = 1.68, p = .432$ (AIC$_b$ − AIC$_a$ = 2.3), even though Figure 7d descriptively suggested a relevant mindset effect. At first glance, the deliberative mindset appeared to be associated with greater changes in pupil size change than the implemental mindset and the baseline. Yet, the model estimates revealed that this descriptive effect was not statistically significant. The deliberative mindset increased pupil dilation changes over time relative to the baseline by 1.09 [-0.56, 2.74] percentage points (implemental mindset estimate: 0.43 [-1.23, 2.08]). However, a significant interaction of difficulty and mindset on pupil size change was observed. Comparing the model that included difficulty, mindset, and their interaction to the last best fitting model (i.e., with only the fixed effect of difficulty and the random effects) indicated a significant interaction, $\chi^2(10) = 22.40, p = .013$ (AIC$_c$ − AIC$_b$ = -2.4). As before, I estimated separate models for each lottery type. These models failed to indicate mindset effects on the lottery type level, all likelihood ratio test $p$s $\geq .321$. But estimating the effect of decision difficulty separately for each mindset conditions revealed that difficulty was a significant predictor of pupil dilation change in the implemental mindset, $\chi^2(4) = 12.67, p = .013$ (AIC$_{diff}$ − AIC$_0$ = -4.7), and marginally significant for deliberative participants, $\chi^2(4) = 8.93, p = .063$ (AIC$_{diff}$ − AIC$_0$ = -1.0). Yet, difficulty did not affect pupil dilation change in the control condition, $\chi^2(4) = 4.03, p = .402$ (AIC$_{diff}$ − AIC$_0$ = 4.0). Hence, the interaction was driven by the distinct effects of decision difficulty on pupil size change for the different mindset conditions.
Figure 7. Percentage of change in pupil dilation over time, depending on (a) decision difficulty (top-left), (b) maximum outcome category (top-right), (c) zero-outcomes (bottom-left), and (d) mindset condition (bottom-right). Reproduced from: Ludwig, J., Jaudas, A., and Achtziger, A. (2020). The role of motivation and volition in economic decisions: Evidence from eye movements and pupillometry. *Journal of Behavioral Decision Making, 33*(2), 180-195. [https://doi.org/10.1002/bdm.2152](https://doi.org/10.1002/bdm.2152).
For further exploration of the role of outcome magnitude, the lotteries were re-categorized based on the maximum outcome in each gamble. Note that earlier work examined mean expected values as a predictor of pupil dilations in risky choices. The median maximum outcome of all 40 lotteries was E135. Lotteries in the lower quartile, i.e., the ten lotteries with the smallest maximum outcome (E < 76.25) were categorized as small outcome lotteries. Correspondingly, the upper quartile lotteries, the ten with the greatest maximum outcome (E > 575) were labeled as large outcome lotteries. The remaining lotteries were categorized as medium outcome lotteries. Figure 7b displays the percentage of pupil size change depending on the lotteries’ maximum outcome category, i.e., small, medium, or large. Visual inspection suggested that larger maximum outcomes were associated with greater sizes in pupil size change over time. A linear mixed-effects model was conducted to test whether this was statistically significant. The maximum outcome category was entered as a fixed effect, lotteries, participants, and bins as random effects, and this mixed-effect model was compared to a reduced baseline model (only random effects). The likelihood ratio test indicated that the maximum outcome category determined pupil dilation change, $\chi^2(2) = 7.77$, $p = .021$ ($\text{AIC}_{\text{maxout}} - \text{AIC}_0 = -3.8$). Relative to large outcome lotteries, changes in pupil size were reduced for medium outcome lotteries by $-0.29$ [-0.63, 0.05] percentage points, and also for small outcome lotteries (relative to large outcome lotteries) by $-0.59$ [-0.98, -0.19] percentage points. This finding corroborated the assumption that pupil dilation reflected the desirability (i.e., the attractiveness of large outcomes) rather than difficulty in decisions under risk.

However, another feature of the lottery choice task could explain the observed pattern of different pupil size changes over time. Among the lotteries that elicited the greatest pupil size changes were lottery types that included zero-outcomes (I, II, IV). The analysis of how fixations were distributed across the four outcomes of one lottery

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6 The results corresponded to prior work (Fiedler & Glöckner, 2012, Study 2) if lotteries were categorized based on the mean expected value (EVmean). However, there was no difference for the change in pupil dilation between medium EVmean and small EVmean lotteries. Given that in the 40 lotteries used in this experiment (see Appendix B) the distribution of EVmean was heavily skewed toward smaller values, this result was not surprising: categorization of lotteries based on quartiles of the EVmean distribution produced small and medium EVmean categories with rather similar properties.
emphasized that zero-outcomes played an important role in pre-decisional information search. As the existence of zero-outcomes was potentially conflated with the analyses of decision difficulty and maximum outcomes, I also compared the change in pupil dilation across lotteries that included a zero-outcome and lotteries that did not, see Figure 7c. A linear mixed-effects model analysis, entering the zero-outcome dummy variable as a fixed effect, revealed a marginally significant effect of zero-outcomes on pupil dilation change, $\chi^2(1) = 2.95$, $p = .086$ (AIC$_{zeroout}$ – AIC$_0 = -1.0$), as indicated by the likelihood ratio test of comparing this model to a reduced baseline model with only the random effects included. When lotteries contained zero-outcomes, there was a tendency that pupils dilated 0.26 [-0.03, 0.56] percentage points more than if no zero-outcomes were included in the lottery.

The effect of zero-outcomes on pupil size change was significant when controlling for the maximum outcome category (by including it as an additional fixed effect in the model), $\chi^2(1) = 7.41$, $p = .006$ (the change in AIC was -5.4, compared to the maximum outcome model). Based on this model, including zero-outcomes (dummy) and maximum outcome category (small, medium, large) as fixed effects, indicated that pupil dilation change was increased by 0.39 [0.12, 0.65] percentage points for zero-outcome lotteries, relative to lotteries that did not contain zero-outcomes. The medium outcome category estimate was -0.43 [-0.75, -0.10], the small outcome category estimate was -0.70 [-1.07, -0.33]; both compared to large outcome lotteries.

**Discussion**

Experiment 2 revealed that lottery choices remained unaffected by the cognitive procedures activated by the deliberative and implemental mindsets. Hence, economic decisions in the lottery choice task were robust across variations of motivational and volitional states of mind. This finding, and the corresponding results from Experiments 1a and 1b, provided converging evidence that there were no direct effects of the deliberative and implemental mindsets on economic decisions. Based on the evidence from these three experiments, the hypotheses H5 and H8 may be rejected with confidence.
Yet, mindsets influenced decision processes, as indicated by the distinct effects of the deliberative and implemental mindsets on decision times and information search. In more detail, Experiment 2 provided evidence that the deliberative mindset was associated with more comprehensive search for information and longer decision times, supporting the hypotheses H6 and H7. Consistent with the hypothesis H10, the implemental mindset led to preferential processing of feasibility-related information (i.e., in the case of lottery choices, this meant a comparatively greater focus on the gambles’ probabilities). Moreover, mindsets also affected the way that decision difficulty determined pupil dilation change over time.

Replicating earlier research (Glöckner & Herbold, 2011; Rahn et al., 2016b; Schotter et al., 2010), it was confirmed that decision times in the lottery choice paradigm increased with decision difficulty. Difficult decisions, in which gamble outcomes were rather similar and their probabilities were in a relatively narrow range, were associated with longer decision times than comparatively more easy lotteries, in which one gamble stood out due to very low or very high outcomes or probabilities.

The eye movement analysis produced results that were consistent with the decision time analysis. Given the naturally occurring very high correlation of fixation count and decision times, this finding was not surprising. Like decision times, the number of fixations per decision increased with increasing level of decision difficulty. Consistent with the predictions (H6 and H7), decision makers in a deliberative mindset tended to make slower decisions and had more fixations than participants in the implemental mindset and control condition. Interestingly, this decelerating effect of the deliberative mindset was most pronounced for very difficult decisions.

This finding supported the general idea that the cognitive procedures that characterize the deliberative mindset carry over to decision processes in subsequent tasks. These carry-over effects may be of particular importance for difficult decisions. Note that even though the results from Experiment 2 suggested that mindsets did not influence choices in the lottery task, this finding may nevertheless have some important implications for decisions outside the laboratory. Consider, for example, complex decisions which entail serious consequences, such as in health contexts. For instance, a doctor faced with the decision whether to perform a surgery that bears some risk of
hazardous consequences could benefit from a deliberative mindset. Specifically, the doctor’s decision may be improved if she took more time to decide and engaged in more thorough search for information, processes which would be supported by a deliberative mindset.

On the other hand, there was evidence consistent with the hypothesis that decision makers in an implemental mindset preferentially processed information related to the feasibility of a goal (H10). Specifically, the fraction of fixations directed at the gambles’ probabilities was higher in the implemental than in the deliberative mindset. This finding, as well, supported the general idea of relevant carry-over effects of the implemental mindset on decision processes in subsequent tasks. Moreover, it supported the hypothesis that after planning where, when, and how to strive for a goal (i.e., in the implemental mindset), information about the probability of an outcome is more strongly processed than after deliberating the pros and cons of a project. This finding, too, could have important implications for real life decision making. For instance, the implemental mindset’s focus on feasibility-related information could improve decisions in managerial contexts in which it is important to remain persistent and surmount implementational obstacles, even if this could prove detrimental to short-term revenues.

Although financial incentives were not systematically varied in Experiment 2, the comparison of the present experiment to earlier work (which used the same lottery choice task but did not offer performance-based incentives) points to three tentative conclusions with respect to the role of financial incentives in the lottery choice task. First, compared with the earlier work in which choices were not incentivized (Glöckner & Herbold, 2011; Rahn et al., 2016b), there was a different rank order of decision difficulty, as defined based on the mean decision times in the five categories of the decision task. Second, even though the mean number of fixations per decision in the present experiment compared well to the earlier research, there was much larger variance in the eye movements. Third, the deliberative mindset appeared to slow down decisions in the present experiment, while Rahn et al. (2016b), who did not offer incentives, reported expedited choices when participants were in a deliberative mindset.

A brief discussion of these effects is in order. Regarding the different rank order of decision difficulty, it was an interesting observation that rank ordering the mean
decision times of the baseline control condition led to a different decision difficulty ranking in Experiment 2 than in the previous studies (Glöckner & Herbold, 2011; Rahn et al., 2016b), that is: I, II, IV, III, V, instead of the ranking presented in Table 11. In the present experiment, difficult lotteries (IV; categorized as such based on the decision time data in the earlier work) turned out to be less difficult, in terms of average decision times, than lotteries of medium difficulty (III). This finding was remarkable, since the earlier research had consistently reported longer decision times for type IV lotteries than type III. Because one major difference between the present experiment and the earlier research was the performance-based incentivization of lottery choices in the present work, it seemed natural to conclude that this different rank order of decision difficulty could have been influenced by economic considerations such as the expectation of monetary rewards. In fact, when choices had real consequences in terms of earnings, this seemed to affect the difficulty of type III decisions, in particular. In this category of the decision task (see also Table 10 and Appendix B), a medium outcome was certain in one gamble and a high gain was risky in the other gamble. When choices had real consequences, this seemed to increase the difficulty of these lotteries (as indicated by increased decision times), compared with a fixed payment regardless of choice outcomes. In other words, it became more difficult to choose between a conservative investment and a high-risk, high-return strategy when the decision makers’ own money was at stake.

Information search patterns and, in particular, the number of fixations per decision, also appeared to be affected by the incentivization of lottery choices. In Experiment 2, there was an increase in the variability of the number of fixations per decision compared with earlier studies (Glöckner & Herbold, 2011; Rahn et al., 2016b). This observation was particularly surprising because conventional wisdom in economics holds that financial incentives reduce performance variability in decision making (Hertwig & Ortmann, 2001; V. L. Smith & Walker, 1993). Among economists, this assumption is usually taken as a strong case for the use of performance-based incentives in laboratory experiments (e.g., Gneezy et al., 2011; Uto, 2017), although some earlier work had cast doubt on whether the assumption of reduced error variance is tangible (Wilcox, 1993). The findings from Experiment 2 suggested that incentives may actually lead to an increase in performance variability, corroborating the skeptical position. It should be noted, however, that a second difference between the present experiment and
the previous research on the same lottery choice task could as well account for the increased variability of eye movements. That is, the on-screen position of all pieces of information (i.e., the eight gamble attributes of one lottery) was fully randomized in the present experiment but not in the previous research by Glöckner and Herbold (2011) and Rahn et al. (2016b). Therefore, as opposed to these latter studies, participants in Experiment 2 could not develop sequential information search strategies relying on the anticipated on-screen position of gamble information.

For instance, it was not possible to always look at the information closer to the horizontal center line first with the aim to check the outcomes of Gamble A versus Gamble B. This information had to be searched for anew on every trial, since participants did not know where the outcomes and probabilities would be presented from lottery to lottery. Therefore, fixations might have ended up being more broadly distributed than in previous studies. However, the fact that decision makers, on average, used about the same number of fixations per decision as in the previous studies is then hard to explain. One would expect that increased difficulty due to the changes in task demands would not only influence the distribution of fixations across the screen, and their variability between participants, but also increase the mean number of pre-decisional fixations required to make a lottery choice. Alternatively, the incentive could have resulted in a more widespread search for information because participants wanted to collect all available information before they made a decision that had consequences for their earnings.

The third indication of possible incentive effects was the finding that choices tended to take longer in the deliberative mindset compared to the control condition. This result was consistent with the hypothesis of slower decisions in the deliberative mindset, due to more extensive information search in this state of mind. It was also in line with earlier evidence of slower goal accomplishment in the deliberative mindset (relative to the implemental mindset; V. Brandstätter et al., 2015). But note that the task in the study by V. Brandstätter et al. (2015) involved a much longer period of time. That is, participants in this study were asked to return a questionnaire to the experimenter within a two-week deadline. Hence, the task was very different from the relatively quick decisions in Experiment 2, and the finding of slower task accomplishment in the deliberative mindset should be linked to the economic decisions in the present experiment.
only with caution. More importantly, though, Rahn et al. (2016b) observed that lottery choices were slower in the implemental mindset than the deliberative mindset when no financial incentive was provided for task performance. Therefore, it can be argued that the decelerating effect of the deliberative mindset on decision processes may be contingent on financial incentives, i.e., real consequences, and hence was not found in the earlier study by Rahn et al. (2016b) despite its similarity in terms of the experimental manipulation and lottery choices. Hence, this finding suggested an interactive effect of the deliberative mindset and financial incentives, as predicted by the hypothesis H11 and as found in Experiment 1a.

With respect to pre-decisional information search in decisions under risk, an interesting finding was that zero-outcomes were largely disregarded. Consistent with prior research (E. Brandstätter & Körner, 2014; Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011), outcomes that entailed no gain at all, i.e., zero-outcomes, were substantially less fixated than any other outcome available on the screen. This finding might not seem too surprising at first glance, given that zero-outcomes are the only pieces of information that were not required to be integrated with probabilities in order to determine the expected value of a gamble’s outcome.

Yet, there could also be different explanation for why decision makers paid so little attention to zero-outcomes and instead rather allocated attentional resources to information that was more relevant in terms of potential gains. Consistent with prior evidence of selective information search based on the anticipated hedonic quality of the information (Karlsson et al., 2009), the finding of reduced attention to zero-outcomes may contribute to the recent debate about a so called zero effect in decisions under risk (Incekara-Hafalir & Stecher, 2016). According to the zero effect, systematic violations of expected utility theory can be explained by the decision makers’ aversion to zero-outcomes rather than a widely presumed preference for certain outcomes (e.g., Kahneman & Tversky, 1979; see the working paper by Incekara-Hafalir & Stecher, 2016, for a more comprehensive elaboration of the zero effect in risky choices).

A particularly surprising finding was that the observed attentional disregard of zero-outcomes was accompanied by greater changes in pupil dilation than other types of lotteries. This was a striking observation because it was previously reported that in
decisions under risk, pupils dilated as a function of the lotteries’ mean expected value (Fiedler & Glöckner, 2012) and in relation to decision uncertainty (Urai et al., 2017). Zero-outcomes do not contribute to a lottery’s mean expected value, nor to decision uncertainty in particular. So, the finding that they elicited greater changes in pupil dilation came as a surprise. One possible explanation for this finding relied on the role of affect in modulating motivational processes and the allocation of attentional resources in economic decisions. Both large outcomes, which more likely occur in lotteries that have relatively high mean expected values, and zero-outcomes could evoke high arousal states but different motivational action tendencies. Large outcomes, or high expected value lotteries more generally, might elicit approach behavior and therefore also attract more attention, while zero-outcomes trigger avoidance reactions and facilitate the allocation of attention to alternative options with more attractive consequences. In both cases, though, high levels of arousal associated with these distinct motivational tendencies would be indicated by an increase in pupil size change in response to the lotteries.

Connecting the finding that zero-outcomes drew less attention than other outcomes to the observation that they elicited relatively strong pupillary responses, it could be concluded that pupil dilation reflected arousal rather than effort during decisions under risk. This seemed evident because processing the information that a gamble included the option to gain nothing could be expected to be rather effortless but highly arousing. High arousal would be expected, in particular, if, zero-outcomes were interpreted like losses in an otherwise gains-oriented decision environment, and thereby triggered negative affect (as suggested by Karlsson et al., 2009). Processing large outcome information, on the other hand, should be rather effortful (assessing the probability of winning this outcome) and at the same time also arousing (evaluating the desirability of that incentive). If both types of gambles, i.e., zero-outcome and large outcome gambles, in fact elicit similar pupillary responses, it seems evident that this should be because pupil dilation tracks arousal rather than effort. The investigation of zero-outcomes in decisions under risk could thus inform to the ongoing debate in psychophysiology about the contributions of arousal and effort to pupillary response (e.g., Kinner et al., 2017). The examination of different gamble attributes and their effects on pupil dilation change thus opens promising avenues for further research to foster our understanding of the affective and motivational processes underlying economic decisions,
and it may also enhance our understanding of the psychophysiological underpinnings of decision making more generally. I will take up this line of argument in the following chapter.

As noted above, it is a common finding in decision research that choices are predicted by eye movements, and particularly by the final fixation, with roughly 70% accuracy (Orquin & Mueller Loose, 2013). For instance, Stewart et al. (2016) showed that eye movements were consistently associated with choices when decision makers chose between two simple gambles. The association of eye movements and decisions was independent from the gambles’ outcome structure. That is, decision makers fixated the gamble they chose more often, and they did so independently of the probabilities and outcomes they saw. In the present experiment, it was revealed that the deliberative mindset increased the predictability of risky choices by eye movements: the final fixation predicted choices with 80% accuracy when decision makers were in a deliberative mindset, whereas the match of the final fixation and the chosen gamble was only 73% in the implemental mindset, and 76% for participants in the control condition.

This finding had two important implications for theory development in research on decisions under risk. First, it emphasized the importance of visual attention in determining economic decisions and echoed the calls for an integration of attentional processes into formal choice models. One recent theoretical innovation that accounts for attentional processes in decision making is the attentional drift diffusion model (aDDM; Krajbich et al., 2010; Krajbich, Lu, Camerer, & Rangel, 2012; Krajbich & Rangel, 2011; S. M. Smith & Krajbich, 2019; Tavares et al., 2017). The aDDM models decision processes as noisy diffusion processes of evidence accumulation and suggests that visual fixations modulate the process of value integration in a way that evidence accumulation is biased in favor of the information that is being fixated at any point in time during the decision making process. Hence, the model incorporates visual attention as a key component of the decision making process.

The aDDM predicts that the final fixation should reliably predict decisions (Krajbich et al., 2010, p. 1294; Tavares et al., 2017, p. 9), among a number of further predictions about the relation of eye movements, decision times, and choices. While this prediction was supported by Experiment 2, the data also supported the assumption that
the attentional processes outlined in the model may be subject to variations in motivational and volitional states of mind. Hence, the second implication was that formal choice models may benefit from the integration of motivational and volitional processes, as described by the deliberative and implemental mindsets. I argue with Wedell (2015) that future research should consider these influences that are so far not represented in formal choice models. Their integration could foster our understanding of the psychological underpinnings of decisions under risk, and economic decisions more generally, and could yield even more precise predictions regarding the relation of choices, decision times, and eye movements.

To follow up on this idea, I took a closer look at some of the predictions of the aDDM. The eye movement data obtained from Experiment 2 not only facilitated a test of the hypotheses about mindset effects on decision processes, as reported above, but also allowed for a test of these aDDM predictions. For instance, Krajbich and Rangel (2011, p. 13854) posited that “the duration of the final fixation should be correlated with the excess amount of time that has been spent looking at the nonchosen items before that fixation”, and that “the final fixations should be shorter than other nonfinal ‘middle’ fixations”. Both predictions were confirmed in a number of studies (see also Krajbich et al., 2010; Tavares et al., 2017).

Notably, I reported above (see Section: Eye tracking data quality) that the mean duration of other, non-final fixations (excluding the first fixation) was considerably longer in Experiment 2 than the mean duration of the last fixation ($M_{\text{last}} = 425.92$ ms, compared with $M_{\text{rest}} = 228.22$ ms). This finding was consistent with a previous eye tracking study of risky choices (Stewart et al., 2016) and appeared to blatantly contradict the aDDM prediction. Yet, this seemingly paradoxical evidence could be attributed to a technical artifact. In Experiment 2, eye tracking raw data sampling for the final fixation continued until the next eye movement was registered (typically, a saccade). That is, samples of eye tracking data were assigned to the final fixation even if the choice had been made and a blank screen was presented, for so long as the participant kept looking at the same position on the monitor. Presumably, in the experiments by Krajbich and colleagues (2010; 2012; 2017), the measurement of the final fixation was terminated in the moment of the decision. The moment of the decision was likely indicated by some
motor activity (e.g., a button press by the participant) and then the measurement of the final fixation was automatically terminated by the experimental software. In fact, when not measuring the final fixation beyond the moment of the decision (as was the default setting for Experiment 2), its mean duration was shorter than that of the other fixations in Experiment 2, too. In that case, the duration of the final fixation was reduced to $M_{\text{last}} = 171.15 \text{ ms (SD} = 152.96)$. That is, the final fixation was indeed shorter than other, non-final fixations; but only if the measurement was aborted by the experimental program. Yet, if the final fixation was measured beyond the moment of the decision, there might be a moment of inertia in the eye movements, rendering the final fixation relatively long. This was the case in Experiment 2 and, presumably, also in earlier work reporting similar results (Stewart et al., 2016).

Regarding the aDDM prediction that the duration of the final fixation should be related with the total duration at looking at the non-chosen option, I correlated the duration of the last fixation (terminated in the moment of the decision) and the total duration of all fixations to the nonchosen gamble. There was a significant overall correlation, $r(3640) = .06, p < .001$. However, computing the correlation coefficients separately for the mindset conditions revealed that the overall correlation was driven by the implemental mindset, $r_{\text{imp}}(1240) = .16, p < .001$, while it was not significant in the control condition, $r_{\text{conf}}(1200) = -.01, p = .815$, and the deliberative mindset, $r_{\text{imp}}(1200) = .01, p = .723$. This aDDM prediction appeared to hold only for decision makers in an implemental mindset.

Taken together, there is initial evidence for the idea that the decision processes modelled by the aDDM may be subject to influences of motivational and volitional processes. This is evidenced by the differential effects of the deliberative and implemental mindsets on outcomes predicted by the aDDM (like the match of the final fixation and the decision), and the fact that (at least some of) the aDDM’s predictions do not seem to equally hold for the deliberative mindset and the implemental mindset alike. This novel finding pointed to the possibility of systematic impacts of motivation and volition on attentional decision processes beyond the effects on decision times, information search, and pupil dilation described above. It also emphasizes the necessity to extend formal models of economic decisions to afford the integration of these influences.
To conclude the discussion of Experiment 2, it should be noted that one limitation of the present experiment was that the incentives were not systematically varied. Thus, the possibility to infer causal effects of financial incentives on economic decisions and their processes remained restricted. Yet, one recent study that used the same paradigm (Rahn et al., 2016b) did not differ from the present experiment in any other aspects of the experimental protocol than the incentive system and the visual display of the lotteries. Therefore, the comparison of results from this study and the present experiment may be consulted to inform the debate about incentive effects in decisions under risk. Moreover, the control condition at large resembled the results by Glöckner and Herbold (2011) who also used the same lottery choice task but did not provide financial incentives. Given the differences regarding automatic decision processes found between the present experiment and the previous research, I am confident to conclude that these distinct findings could be, at least partially, attributed to the presence of performance-based financial incentives.

Finally, the way decision difficulty was defined in the present experiment could be criticized. The definition of difficulty was not rooted in the experimental material itself but instead relied on decision time data from previous studies. Besides the fact that a definition of difficulty that is based on the distinctive features of different categories of the decision task, i.e., the different types of gambles, would be preferable, it remained an open question whether the mean decision times of different types of lotteries could be appropriately mapped on a dimension of decision difficulty. This is because the observed differences in decision times could also be attributed to task desirability, familiarity, or other features that potentially distinguish between the different types of lotteries.
This chapter explores the zero effect in risky choices. It reports an experiment that was inspired by, and designed as, a follow up study to the surprising finding from Experiment 2 that zero-outcomes, on the one hand, were disregarded in terms of visual attention, but on the other hand, evoked pupillary responses similar to those typically observed for lotteries with high expected values (Fiedler & Glöckner, 2012). In this chapter, I follow up on this interesting observation and explore its relation to a recently described choice regularity in decisions under risk that has been coined the zero effect (Incekara-Hafalir & Stecher, 2016). According to the zero effect, commonly observed deviations from expected utility theory may be explained by the decision makers’ aversion to receiving zero-outcomes, rather than their attraction to certainty, i.e., sure gains in the lottery choice paradigm. Incekara-Hafalir and Stecher (2016) first described this phenomenon in a recent working paper that addressed one of the most studied choice regularities in decision research, the common ratio effect.

The common ratio effect introduced by Allais (1953) describes one of the most striking violations of expected utility theory. Consider, for instance, the choice between a sure win of $3000, and a gamble offering an 80% chance to gain $4000 or, if unsuccessful, gain nothing. Typically, a clear majority of decision makers prefers the sure gain. For instance, Kahneman and Tversky (1979) reported that 84.2% opted for it, a suboptimal choice regularity coined the certainty effect. Now consider a second lottery choice, in which participants must decide between one gamble that offers a 25% chance of gaining $3000 (or else gain nothing) and another gamble that offers a 20% chance of

7 The experiment presented in this chapter is included in a manuscript entitled “The zero effect in risky choices” (Ludwig, J., Jaudas, A., & Achtziger, A.), which is currently (June 2020) being prepared for peer review.
gaining $4000 (or else nothing). Since this problem is different from the first one only in that its probabilities are scaled down by a common factor of .25, expected utility theory implies that decision makers who preferred the sure option in the first problem should also opt for the safer gamble in the second problem. Kahneman and Tversky (1979) reported that 68.4% chose the risky option, demonstrating a striking preference reversal when scaling down gambles by a common factor.

The common ratio effect was replicated numerous times (Ballinger & Wilcox, 1997; Barron & Erev, 2003; Baucells & Heukamp, 2010; Loomes & Sugden, 1998) and remained robust for risky choices. But note that it can be reversed under certain conditions (Blavatskyy, 2010) and that it seems susceptible to variations of framing (Harless, 1992; Harman & Gonzalez, 2015) and the decision domain (M. Schneider & Shor, 2017). The conventional explanation for the common ratio effect is that probabilities differ in their impact on the valuation of prospects. In cumulative prospect theory (CPT), this idea was formalized as the probability sensitivity parameter (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). It captures diminishing sensitivity to probabilities with increased distance to certainty, i.e., decision makers are more sensitive to changes in probabilities near zero and one (certainty) than they are to changes of intermediate probabilities. This provides an explanation for the common ratio effect, and for the certainty effect, elucidating why decision makers generally prefer sure gains over risky gambles, even if the former have lower expected utility.

As briefly mentioned above, an alternative explanation for the Allais Paradox has been suggested recently (Incekara-Hafalir & Stecher, 2016). Decision makers’ systematic violations of expected utility theory in Allais-type decision problems need not be rooted in diminishing sensitivity to probabilities but can instead be explained by an aversion to receiving zero-outcomes. That is, decision makers might be motivated to avoid outcomes that offer no gain at all. This avoidance motivation might suffice to explain commonly observed violations of expected utility theory like the certainty effect (Incekara-Hafalir & Stecher, 2016). In fact, many studies on this issue, including the seminal work by Kahneman and Tversky (1979), contrasted sure gains with an option that included the risk of gaining nothing. This lottery choice setup cannot differentiate between the contributions of the certainty effect and the zero effect to the observed choice patterns. It remains ambiguous regarding the interpretation of choice preferences. In particular, the
proclaimed certainty effect could be confounded with an aversion to receiving zero-outcomes.

In this chapter, this line of research is extended by a deeper exploration of the zero effect in decisions under risk. That is, I further explored the possibility that decision makers presented with paradigmatic lottery choices were motivated to avoid zero-outcomes rather than being attracted to certainty. In an otherwise gains-dominated decision environment, an outcome as aversive as a zero-outcome should receive particular weight in decision making.

It was proposed that automatically triggered avoidance reactions elicited by zero-outcomes would determine risky choices, perhaps more so than sure gains when both were included in a lottery. In this sense, the zero effect could be relatively stronger than the certainty effect when both were in conflict. The rationale was as follows. In principle, sure gains might appear particularly attractive because they occur with certainty. Hence, choosing the sure option over an alternative risky gamble would minimize the decision risk. Assuming that decision makers generally are, to some degree, risk averse (e.g., Holt & Laury, 2002), and that probabilities are not represented linearly in decisions under risk (Kahneman & Tversky, 1979), preference for the sure gain seems natural. But when a sure gain is pitted against a zero-outcome, decision makers might opt for the sure gain because they are motivated to avoid receiving the zero-outcome, rather than being attracted to the sure gain.

This consideration is in line with another crucial feature of the CPT, namely that “losses loom larger than gains” (Kahneman & Tversky, 1979, p. 279). Decision makers generally seek to avoid losses, and they do so more than seeking to acquire equivalent gains (see also Tversky & Kahneman, 1992). Assuming that zero-outcomes are considered losses when all other outcomes are in the domain of gains, these outcomes should have comparatively greater weight for decisions than any other outcome, even if the latter were sure gains. Put differently, a zero-outcome in the gain domain might be experienced as a loss even though participants do not actually lose anything. They just do not gain money in the case of a zero-outcome. In this sense, gaining nothing, by receiving a zero-outcome, may in fact sometimes feel like losing. Decision makers might experience zero-outcomes as losses when all other outcomes are gains, as their
expectancies of obtaining at least some money in a lottery (even if only a rather small amount of money) are frustrated.

Note that the distinct motivational tendencies elicited by zero-outcomes, in comparison with outcomes that occur with certainty, can be expected to be reversed in the loss domain. If zero-outcomes were appraised as gains in an otherwise loss-dominated decision environment, then a zero-outcome is clearly the most attractive option. Consequently, decision makers should opt for the zero-outcome when it is pitted against a sure loss in the loss domain. In this case, decision makers could be attracted to the option that allows them to evade any loss, rather than being driven to avoid a sure loss. In the present experiment, I did not investigate the effects of zero-outcomes across the domains of gains versus losses, but instead disentangled the contributions of the certainty effect and the zero effect to decisions under risk in the gain domain.

In tackling the question of whether the certainty effect or the zero effect would predominate when both were pitted against each other, behavioral lottery choices were examined but I also focused on the attentional processes underlying the presumed zero-outcome aversion outlined above. This approach was inspired by the recent debate about information processing in decisions under risk, claiming a crucial role of visual attention in economic decisions (e.g., Bordalo et al., 2012; Krajbich et al., 2010; S. M. Smith & Krajbich, 2019; see also Chapter 6 of this dissertation).

Some earlier research has already examined how attention is allocated to zero-outcomes (or sure gains) in risky choices. It was reported that zero-outcomes typically received comparatively less attention than other gamble attributes in gain, loss, and mixed domain lotteries (e.g., E. Brandstätter & Körner, 2014; Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011; Pachur, Schulte-Mecklenbeck, Murphy, & Hertwig, 2018). One recent article, for example, described the acquisition frequencies of zero-outcomes in a MouselabWEB experiment (Pachur et al., 2018). Although not analyzed in detail, the authors reported that zero-outcomes and their probabilities were substantially less frequently acquired than any other information included in the lotteries (Pachur et al., 2018, see Appendix). This finding was consistent with earlier work demonstrating similar patterns of selective attention allocation to zero-outcomes (E. Brandstätter & Körner, 2014; Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011; see also Experiment
2 of the present dissertation). Presumably, zero-outcomes were easier and quicker to process and thus drew less attention than non-zero outcomes. The reason for this might be that zero-outcomes are not worthwhile of being integrated with their probabilities as they do not provide any (desirable) value for a decision maker. Thus, there is no need to seriously consider them in the decision process.

However, an alternative explanation of why zero-outcomes are looked at less than other outcomes based on the zero effect described above implies a greater weighing of zero-outcomes than that of non-zero outcomes in the decision process. Conceivably, an aversion to receiving zero-outcomes could influence attentional processes. It might prompt decision makers to disregard zero-outcomes and to deploy attention to more attractive information (i.e., gains) instead. These processes would be functional when zero-outcomes in otherwise gains-oriented decision environments were interpreted like losses that should be avoided at any costs. In this case, zero-outcomes might be ignored, and attention should be deployed to other gamble attributes in order to assess the alternative option’s expected utility.

Note that these two possible explanations for reduced attention to zero-outcomes entail different predictions regarding the affective and motivational processes triggered by zero-outcomes. Under the explanation that zero-outcomes were simply easier and quicker to process because they did not require integration with probabilities, one would not expect these outcomes to generate any specific affective experience or motivational tendency (e.g., approach or avoidance). On the other hand, if decision makers eschewed these gamble attributes due to a strong aversion to receiving zero-outcomes, higher arousal and a pronounced avoidance tendency could be expected.

There seems to be no research so far that tested these competing approaches to explaining selective attention effects of zero-outcomes. Moreover, there is only very little research to date that explicitly addressed the question of competition among the certainty and zero effects and their relative contribution to decisions. In particular, there is not much research on risky choices in which the certainty effect and the zero effect were in conflict. In fact, there seems to be no research on the zero effect in risky choice, which assumes an automatic avoidance reaction prompted by zero-outcomes, except for a working paper by Incekara-Hafalir and Stecher (2016).
Some initial evidence for the notion of a specific affective and motivational response to zero-outcomes compared to non-zero comes from the behavioral finance literature on the ostrich-effect. Karlsson, Loewenstein, and Seppi (2009; see also Galai & Sade, 2006) argued and found that pre-decisional information acquisition was driven by the hedonic quality of information, and that attending to information would increase the psychological impact of that information. Accordingly, Karlsson et al. (2009) reported that investors monitored their portfolios more actively in the case of rising markets but, like the ostrich, they “put their heads in the sand” and avoided gathering additional information when markets were flat or falling. Given that decision makers faced with risky choices seek to reduce the negative affect elicited by a zero-outcome information in an otherwise gains-dominated decision environment, it would be rather unpleasant for them to gather additional information on that zero-outcome by allocating more attention to it than to other (more pleasant) information.

Accordingly, it could be argued that in order to diminish the upcoming disappointment about the risk of receiving nothing when being confronted with zero-outcomes in risky choices, decision makers might be inclined to simply ignore that option. That is, in terms of visual attention, it would be expected that zero-outcome lotteries (and zero-outcomes in particular) draw comparatively less attention than other gamble attributes. This selective attention effect should also translate into a choice bias, i.e., zero-outcomes included in one gamble should bias choices toward the other gamble.

This specific role of affect in guiding the deployment of attentional resources to zero-outcomes received initial support from the findings presented in the previous chapter on Experiment 2. Consistent with prior research, it was observed in Experiment 2 that zero-outcomes, relative to other gamble attributes, received substantially less visual attention during information search in a lottery choice task (see also E. Brandstätter & Körner, 2014; Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011). It was further revealed in Experiment 2 that zero-outcomes were associated with increased pupil size, compared with lotteries that did not contain zero-outcomes. This effect remained robust when controlling for lotteries’ mean expected values (see Fiedler & Glöckner, 2012) and suggested that zero-outcome lotteries were comparatively more arousing. Increased arousal could not be expected if zero-outcomes were simply easier to process than other lottery outcomes because expected utility considerations were not required in
this case (i.e., zero multiplied with any probability \( p \) always ends up resulting in an expected utility of zero). Hence, Experiment 2 tentatively concluded that higher arousal in response to zero-outcome lotteries might be caused by the decision makers’ interpretation of zero-outcomes as losses.

Experiment 3 further investigated the mechanisms presumably associated with the processing of zero-outcomes in risky choices. The first objective of this experiment was to disentangle the contributions of the certainty effect and the zero effect to decisions under risk (i.e., decision behavior). Second, I concentrated on the psychological mechanisms underlying the selective attention allocation to zero-outcomes. This was an attempt to rule out the explanation that zero-outcomes draw less attention simply because the value zero does not require to be integrated with its probability in making a lottery choice.

The remainder of this chapter is organized as follows. In the following section, I will first briefly consider the earlier work that examined if and why the number zero might be of particular importance in decision making. Next, I describe in detail the approach to test the ideas outlined above in Experiment 3, before turning to the report of that experiment. Finally, this chapter concludes with a discussion of the experimental findings and a tentative outlook for promising areas of future research.

The number zero in judgment and decision making

Zero is a curious number, and people tend to react to it even more curiously. Take, for example, free products, i.e., products with a price of zero. Shampanier, Mazar, and Ariely (2007) reported a series of experiments in which decision makers chose between two pieces of chocolate candy, one of which was free. In hypothetical and in real buying situations, people overreacted to the price of zero. When the price was reduced to zero, this did not only increase the demand for that chocolate, but participants now preferred the free chocolate over another one that was also reduced in price by the same amount and that had been preferred prior to the reduction of prices. That is, their decision was not simply guided by the fact that the chocolate was now free, but the zero-price effect even generated a change of preferences for these products. Decision makers did not only react
to the reduced cost of buying, but the perceived benefit of the free chocolate was increased relative to the same chocolate if they had paid for it. Consequently, Shampanier et al. (2007) argued that a zero-price tag elicited a more positive affective evaluation of the product than any other price could, and that this affective response served as a heuristic cue for decision making when choosing between several products (see also Bateman et al., 2007; Finucane, Alhakami, Slovic, & Johnson, 2000).

Recent brain-imaging work supported the idea that affect gave rise to the zero-price effect (Votinov, Aso, Fukuyama, & Mima, 2016), which in addition, is not confined to binary food choices but more broadly generalizable to consumer decisions (Mazar, Shampanier, & Ariely, 2016; Nicolau, 2012; Nicolau & Sellers, 2012; Palmeira, 2011). For instance, Nicolau and Sellers (2012) demonstrated a zero-price effect in multi-attribute tourism choices. In these experiments, the demand for a hotel increased when a free breakfast was included, while it decreased for another hotel that was initially preferred over the former.

Another case for the uniqueness of the number zero is made by motivation research. Relative to an attractive reward, no reward at all (i.e., a zero-outcome) can increase the appraisal of a target experimental task, as well as performance in it (Festinger & Carlsmith, 1959; Lepper et al., 1973). For instance, Gneezy and Rustichini (2000b) reported that participants answered less IQ-test questions correctly when offered a small reward for accuracy, compared to a no-reward condition (but performance increased when the reward was high). Further research showed that the number zero is special in that it represented an exception to the predicted linearity of the effects of, for example, social norms (Heyman & Ariely, 2004) or punishment (Gneezy & Rustichini, 2000a). In a field study, Gneezy and Rustichini (2000a) showed that introducing a monetary fine for tardiness of picking up their children from the day-care center increased the number of late-coming parents, instead of reducing tardiness. Heyman and Ariely (2004) conducted a series of experiments to explain why people sometimes make a greater effort when they do not receive any compensation than they would for a low payment. The results indicated that the relation between effort and payment was determined by both the magnitude of the payment and the kind of market (social vs. monetary), and that social markets were less sensitive to the absolute amount of the compensation than monetary markets.
Most importantly for the present research, Tversky and Kahneman (1979, 1992) demonstrated the exceptional nature of the number zero in the context of risky choices. When choosing between lotteries like the ones mentioned above, probabilities of zero (and one) were perceived accurately, as opposed to intermediate probabilities that were distorted by diminishing sensitivity to probabilities further removed from certainty. Thereby, decision makers underestimate medium and large probabilities and tend to opt for sure gains (i.e., gains with a probability of one) whenever available, even if their expected value is smaller than that of risky alternatives. As mentioned above, this CPT-based explanation of the certainty effect was recently challenged by another attribution of exceptionality to the number zero. Incekara-Hafalir and Stecher (2016) reported initial evidence for the idea that decision makers’ systematic violations of expected utility theory in Allais-type decisions could be driven by an aversion to receiving zero-outcomes rather than by an attraction to certainty.

Experiment 3

Experiment 3 extended this line of research in order to disentangle the unique contributions of the certainty effect and the zero effect to decisions under risk. For this purpose, choice data was collected in a lottery choice task explicitly designed to pit the two effects against each other. A second objective was the exploration of the attentional processes underlying these effects through eye tracking. Learning about these attentional processes could contribute to the clarification of the relative strength of both the certainty and the zero effect in decisions under risk, especially when they conflicted with each other. Eye movements were recorded as indicators of pre-decisional information search to get a richer data basis for testing hypotheses about the relative impact of specific gamble attributes (such as sure gains or zero-outcomes) on choices and decision processes under risk. This approach facilitated the analysis of whether specific gamble attributes would dominate pre-decisional information acquisition and downstream decision processes. Moreover, the process data (i.e., fixations and pupil dilations) promised to shed light on the psychological mechanism underlying the effect of selective attention to zero-outcomes. This data could be used to test whether zero-outcomes would be neglected in decisions under risk in the gain domain just because they are easier to process as they do
not require the integration of probabilities to calculate expected utilities, or if zero-outcomes were also associated with increased arousal. This would point to a strong aversion to receiving zero-outcomes, as suggested by the zero effect. Hence, two primary aims were pursued in Experiment 3. First, I intended to clarify the roles of the certainty effect and the zero effect in determining risky choices. The second aim geared at identifying the attentional processes underlying these effects.

A lottery choice task was designed in which decision makers chose between two gambles (of equal or close-to-equal mean expected values, so that no preferences based on expected values could emerge). Some of these gambles included zero-outcomes, and some represented sure, or almost sure gains. The experimental material was configured in a way that the certainty effect and the zero effect on lottery choices could be investigated independent of the other. For instance, lotteries that included a sure gain in one gamble did not include a zero-outcome in the other gamble (e.g., CERT\textsubscript{100} lotteries, see Method section). If decision makers preferred the sure gain over a risky gamble in this type of lottery, it could be concluded that this preference relied on the attractiveness of the sure gain and not because decision makers tried to avoid a zero-outcome. Importantly, since zero-outcomes were not included in all lotteries that included sure gains, conclusions about the processes underlying the choices were not confounded with decision processes triggered by the presence of zero-outcomes. Additionally, a zero-outcome lottery type was included which did not provide a large gain with certainty (ZERO lotteries; see Method section). If choice proportions in this lottery type were biased toward the non-zero option, this could be unmistakably attributed to the decision makers’ aversion to receiving zero-outcomes.

Finally, in one category of the lottery choice task (CERT\textsubscript{ZERO}), the certainty effect and the zero effect were pitted against each other. This was done to examine which gamble attribute (sure gain vs. zero-outcome) dominated a decision if a situation activated opposing motivations, i.e., avoiding the zero-outcome and approaching the sure gain. That is, CERT\textsubscript{ZERO} lotteries presented an almost sure gain and a zero-outcome in the same gamble. In other words, in these lotteries the certainty effect motivated to choose this option, while the zero effect motivated to avoid the very same option. All lottery types and their key features are shown in Table 13 and discussed in more detail in the Method section.
Table 13  
*Lottery types and key features of the lottery tasks used in Experiment 3.*

<table>
<thead>
<tr>
<th>Lottery type</th>
<th>Key features</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIM</td>
<td>All outcomes are very similar; value according to CPT is similar for both gambles (Glöckner &amp; Herbold, 2011)</td>
</tr>
<tr>
<td>CERT(_{100})</td>
<td>Two equal outcomes for Gamble A (i.e., one 100% certain outcome), certainty effect points to Gamble A</td>
</tr>
<tr>
<td>CERT(_{99})</td>
<td>One almost certain outcome for Gamble A, (almost)certainty effect points to Gamble A</td>
</tr>
<tr>
<td>ZERO</td>
<td>One zero-outcome for Gamble A, zero effect points to Gamble B</td>
</tr>
<tr>
<td>CERT(_{\text{ZERO}})</td>
<td>One zero-outcome and one almost certain outcome for Gamble B, zero effect points to Gamble B, (almost) certainty effect points to Gamble A</td>
</tr>
</tbody>
</table>

As mentioned above, Experiment 3 was designed to scrutinize decisions in the lottery choice task and their underlying processes. The latter were examined through eye tracking. Earlier research had used eye tracking and other process-tracing methods to investigate decision processes under risk (e.g., Fiedler & Glöckner, 2012; Krajbich et al., 2010; Pachur et al., 2018; Stewart et al., 2016). Eye tracking is particularly useful to investigate automatic visual attention processes and their impact on economic decisions because it traces unconscious decision processes. Decision makers are typically not fully aware of all decision processes and cannot deliberately regulate them. Thus, unconscious processes are of a great interest for decision researchers. Since zero-outcomes might impact decisions on the level of automatic processes, measuring eye movements and pupil dilation seemed natural.

It was proposed that zero-outcomes elicit a rather effortless and automatic response of allocating attention toward gamble attributes that were more attractive than zero-outcomes. Presumably, affect played a key role in modulating this response. This reasoning was consistent with the responses to zero prices described above (Shampanier et al., 2007; Mazar et al., 2016; Votinov et al., 2016; see also Bateman et al., 2007; Finucane et al., 2000). While zero prices represented zero-outcomes in the domain of losses (and thus were very attractive attributes of a decision), it could be expected that affect would be equally important in modulating the response to zero-outcomes in...
otherwise gains-oriented decision environments. That is, I assumed that the quick and ostensibly unintentional avoidance of zero-outcomes could be caused by a negative affective reaction to these outcomes.

Along the same lines, the findings from Experiment 2 pointed out that affect might be the key to understanding the zero effect in risky choice. This argument was built on the pupil dilation data reported in the previous chapter. Zero-outcomes evoked pupillary responses similar to the responses observed when decision makers are faced with very attractive lotteries that promise high gains. Despite these similarities in pupil dilation change, which indicated high arousal in reaction to both zero-outcomes and high-value outcomes, the nature of the affect triggered by these different types of lotteries might be quite different. In the case of zero-outcomes, the affective response should be of negative valence, while in the case of lotteries with high gains, affect should be positive. Accordingly, despite similar pupil size changes in response to zero-outcomes and high gains, distinct (i.e., opposing) motivational and action tendencies (avoidance vs. approach) should result from these outcomes. Note that affect-as-information theories (e.g., Schwarz & Clore, 1983) interpret high arousal as an indicator of the intensity of affect, but not as an indicator of valence. The valence of an affective experience could only be inferred from the stimuli presented at the very moment of the pupil change. I followed this idea in the present work. While relatively high value outcomes (e.g., 100 experimental currency units; see below) should evoke approach motivation based on positive valence, zero-outcomes should be associated with negative valence and trigger reactions of avoidance. In terms of arousal, though, these gambles could trigger rather similar patterns since the intensity of the physiological response to these outcomes could be rather similar.

Hypotheses

Based on the prior work on information search in decisions under risk (E. Brandstätter & Körner, 2014; Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011; Pachur et al., 2018; see also Experiment 2), the following patterns of choice proportions, decision times, eye movements (fixations and saccades), and pupil dilations were expected to emerge in Experiment 3. Decision makers should be motivated to avoid
zero-outcomes due to a highly arousing, affective response of negative valence. Note that the prediction of negative affect relied on the lotteries being set in the gains domain and the proposition that zero-outcomes would be treated like losses in this decision environment. Of course, this would be different for lotteries in the loss domain and for mixed-domain lotteries. Experiment 3 examined the role of zero-outcomes in the gain domain only, though.

**Lottery choices.** Negative affect and the resulting avoidance motivation should reduce choice proportions for gambles with zero-outcomes (ZERO and CERTZERO), in line with the notion of a zero effect determining risky choices. Hence, it was expected that choice proportions in these lotteries were reduced substantially below .50, i.e., below the chance probability of choosing one of the two gambles. Incekara-Hafalir and Stecher (2016) challenged the certainty effect more generally by demonstrating that an expected utility model combined with the certainty effect (i.e., modeling the presumed attraction to certain gains) did not outperform the expected utility model alone. Following their line of argument (but contradicting Kahneman & Tversky, 1979), lotteries including sure (probability of one, CERT100) or almost sure gains (probability of .98 or .99, CERT99) should not be selected much more often than by chance, i.e., an expected choice proportion of .50. On the contrary, a conventional certainty effect prediction would be that decision makers should prefer sure gains over risky gambles whenever these are available, leading to increased choices of the sure gain option in these lotteries (CERT100, CERT99). These were reasonable arguments for both predictions. Therefore, I did not claim a specific pattern of choice proportions in these lottery types but remained open to let the data speak to these competing predictions.

Finally, choice proportions should be close to (and not statistically different from) .50 for SIM lotteries since the two gambles in these lotteries were alike in terms of their probabilities and outcomes. That is, these lotteries did not include extremely high or extremely low outcomes (like for instance zero-outcomes), and probabilities ranged between .25 and .75, so that no single gamble attribute stood out to bias choices toward one or the other gamble.

**Decision times, fixations, and saccades.** With respect to the number of fixations during pre-decisional information search, the postulated zero effect should lead to an
attentional disregard of zero-outcomes and their probabilities. This finding was reported in previous research (see above) and I expected to replicate these results. Supposedly, zero-outcomes should be identified rather effortlessly, and a response of avoiding these outcomes should follow automatically (see also Bateman et al., 2007; Finucane et al., 2000). If attentional resources thereby became available, the lottery should be less demanding in terms of information search. Put differently, it should be easier (and quicker) to choose between two gambles when a zero-outcomes was included than it would be when no zero-outcome was involved. Processing lotteries with zero-outcomes should consume less attentional resources than lotteries that require to assess all available information carefully in order to follow expected utility considerations. Hence, I predicted fewer fixations for lotteries with zero-outcomes (ZERO and CERTZERO) compared to lotteries in which all outcomes were higher than zero (e.g., SIM). This prediction, again, represented a replication of prior findings, as for instance in Experiment 2.

Previous research argued that decision times were an indicator of decision difficulty (Achtziger & Alós-Ferrer, 2014; Rahn et al., 2016b; Schotter et al., 2010). Thus, if zero-outcomes were processed more easily than other gamble attributes, decisions should be quicker for lotteries with zero-outcomes (ZERO and CERTZERO) compared to lotteries that do not include a zero-outcome (SIM, CERT100, CERT99).

A related pattern of results was expected for saccades. If zero-outcomes were processed easier and quicker than other gamble attributes, saccades between the zero-outcome of a gamble option and its probability should be rather rare. After perceiving the zero-outcome, contemplating about its attainability would not make much sense since its expected value was zero regardless of its probability (see above). Consequently, fewer saccades within gambles for lotteries with zero-outcomes (ZERO and CERTZERO) were expected compared to lotteries that were quite difficult due to their rather similar probabilities and outcomes (SIM). The latter should require a more intense search for information than lotteries with zero-outcomes.

Note that the above hypotheses about fixations and saccades in relation to zero-outcomes may be inferred from both the explanation that zero-outcomes draw less attention than other outcomes because their expected utility is zero and the explanation
that a zero-outcome promotes avoidance responses. Yet, these explanations differ regarding the predicted patterns of arousal and motivational tendencies triggered by zero-outcomes. If zero-outcomes were avoided based on an ostrich effect-like mechanism, they should evoke negative affect and high levels of arousal (i.e., intensity of this affect). Increased arousal would not be expected if zero-outcomes were simply easier to process.

**Pupil dilation.** Pupillometry provided an option to trace the presumed affective processes underlying the zero effect in risky choice. In general, pupillary responses are influenced by various factors, for instance cognitive effort (Kahneman & Beatty, 1966), arousal due to decision uncertainty (Urai et al., 2017), or cognitive conflict (van Steenbergen & Band, 2013). Changes in pupil dilation can also be interpreted as indicators of the intensity of affect, i.e., arousal more generally (e.g., Hochman, Glöckner, Fiedler, & Ayal, 2016; Kinner et al., 2017). Using a lottery choice paradigm similar to the one in the present experiment, Fiedler and Glöckner (2012) demonstrated that pupils dilated as a function of the lotteries’ mean expected value, presumably because higher mean expected values (and thus, higher gains on average) elicited higher levels of arousal due to their increased desirability. But given the wide variety of the determinants of pupil dilation change over time (see above), it remained unclear whether pupillometry could be used to isolate the affective responses in a lottery choice paradigm (i.e., arousal induced by specific gamble attributes), or whether pupils would rather represent decision difficulty (cognitive effort) or outcome desirability (arousal).

Pupil dilation change over time was examined dependent on the different lottery types used in Experiment 3 in order to explore the alternative explanations for why pupils dilate in response to risky choices outlined above. Prior research described many different determinants of pupil dilation change in decision making (see above). Therefore, and because there was no consensus as to which of these determinants would dominate the processing of zero-outcomes in the gain domain, I refrained from posing specific hypotheses about pupil dilations in response to zero-outcome lotteries versus other lottery types.

Yet, it should be noted that the pupillometric analysis was guided by the findings from Experiment 2. The results from this study suggested that pupil dilations in decisions under risk might reflect arousal (i.e., affect) rather than cognitive effort. As noted above,
the change in pupil size over time (relative to a pre-stimulus baseline) was greatest for lotteries that included either an outcome of very high value or a zero-outcome. Note that participants were paid according to their individual gains in the lottery choice task. Hence, decision makers were highly engaged in the lottery choice task and motivated to increase their payment by optimizing their decisions. Pupils seemed to react most to the gamble attributes that impacted the affective evaluation of the gambles, i.e., very high or null gains, rather than dilating as a function of decision difficulty (i.e., cognitive effort). Based on these findings, it was a tentative conclusion of Experiment 2 that pupil dilation in decisions under risk reflected decision processes shaped by (affective) arousal rather than by cognitive effort. Experiment 3 followed up on this line of argument, sought a replication of the zero effect on pupil dilation, and further explored the role of affect in modulating the pupillary responses to zero-outcomes in decisions under risk.

Method

Participants and design. A target sample size of 33 participants was determined prior to data collection. This target followed the rule of thumb to collect data from at least 30 participants per cell of a between-subjects design (Experiment 3 had a one-factorial within-subjects design). The sample size was in line with sample sizes in comparable eye tracking studies on judgment and decision making (e.g., Fiedler & Glöckner, 2012; Franco-Watkins & Johnson, 2011; Perkovic, Bown, & Kaptan, 2018; S. M. Smith & Krajbich, 2019). Test planning also anticipated the exclusion of participants, for instance due to poor data quality or software errors. In the Hugo-Eckener-Laboratory, roughly 10% of participants must be excluded due to these kinds of errors in eye tracking studies. Hence, thirty-six participants (16 female; $M_{age} = 22.49$ years, $SD = 3.03$) were invited for individual sessions. One participant was excluded from the analysis due to technical problems with the eye-tracker, so the final sample size was $N = 35$. Participation was compensated with €3 plus an additional payment contingent on performance in the decision task. The performance incentive was based on a random lottery incentive system. Participants were informed that one of the lotteries would be chosen and played by the computer, and that their additional payment would be determined by the outcome of this lottery (range: €0.90 to €9.00, $M = €4.17$, $SD = 2.44$).
The experiment followed a one-factorial within-subjects design (lottery type: SIM vs. CERT$_{100}$ vs. CERT$_{99}$ vs. ZERO vs. ZERO$_{CERT}$). The key features of these five lottery types are summarized in Table 13 (see also the Materials section for a more detailed description of each lottery type, and Appendix C for a full list of the lotteries used in this study). There were ten lotteries in each category of the decision task, amounting to a total of 50 lottery choices per participant.

An additional factor for the analysis of fixations was the lottery outcome (within-subjects, outcomes: A1, A2, B1, B2). It was analyzed how fixations were distributed across the four outcomes of one lottery to assess whether zero-outcomes would receive the same share of attention that other outcomes received. For the pupillometric analyses, the lotteries’ mean expected value was added as an additional factor since prior work demonstrated that it determined pupil dilation in risky choices (Fiedler & Glöckner, 2012). Lottery choices, decision times, eye movements (i.e., fixations and saccades), and pupil dilations were recorded as the dependent variables.

The analytical approach relied mainly on mixed-effect models with random intercepts for lotteries and participants in order to account for the variability of eye movements between lotteries and participants. The analyses were based on 1750 observations (35 participants made 50 decisions, respectively). Note that for the analysis of lottery choices, the dependent variable of interest was the choice proportion depending on the lottery type, i.e., choice data was aggregated across trials. A sensitivity power analysis using GPower (Faul, Erdfelder, Lang, & Buchner, 2007) indicated that the minimum detectable effect size in a two-tailed one-sample $t$-test of means difference from a constant was $d = .56$ (assuming $\alpha = .05$ and $\beta = .90$). In a one-factorial repeated measures analysis of variance, the minimum detectable effect size was $f = .333$ ($\eta^2 = .100$), given $\alpha = .05$, $\beta = .90$, and the empirical average correlation of the repeated measures, $r = -.022$.

**Procedure and materials.** Participants were screened for involvement in similar research (specifically, Experiment 2) and hard contact lenses, which would have interfered with the measurement of eye movements. They gave informed written consent prior to data collection. Following detailed instructions on the lottery choice task, participants were familiarized with the eye tracking device, a tower-mounted monocular SMI iViewX XTM Hi-Speed, sampling at a 240 Hz rate. All participants had normal or
corrected-to-normal vision. An LCD-monitor (AOC LM927U, refresh rate 60 Hz, resolution 1280 × 1024) was located 700 mm in front of the participants’ eyes. The SMI iViewX 2.2 software (SensoMotoric Instruments, Teltow, Germany) was used to record gaze data. Choices and decision times were collected using Presentation 17.1 (Neurobehavioral Systems, Albany, CA, USA).

The lottery choice task consisted of five types of lotteries designed to disentangle the contributions of the certainty effect and the zero effect to automatic decision processes and choices in decisions under risk. Based on eight lotteries taken from Glöckner and Herbold (2011), ten lotteries were designed for each category, amounting to 50 lotteries in total (see Table 13 for an overview of the lottery type’s key features, and Table C1 in the appendix for the complete lotteries). Each lottery consisted of two gambles (Gamble A on the left, Gamble B right), and each gamble offered the chance to gain a positive amount of experimental currency units (E) with probability \( p \), or the chance to gain another amount of E with a probability of \( 1 - p \) (probabilities within one gamble always added up to 1). For all types of lotteries, the mean expected values of the two gambles of one lottery was close to or exactly the same, so that preferences for one of the gambles based on higher mean expected values were ruled out.

The first type of lotteries (SIM) was taken from a set of risky choices by Glöckner and Herbold (2011), which was also used for Experiment 2. Two lotteries were added to the original sample of eight SIM lotteries in order to raise the number of lotteries per category to ten. These lotteries were characterized by a high similarity of all outcomes and probabilities (e.g., outcomes ranged from 50 to 69 E and probabilities from .40 to .60 in one lottery of this category; overall probabilities in this category were between .25 and .75). According to cumulative prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), both gambles had very similar subjective utilities (see Glöckner & Herbold, 2011).

Based on the SIM lotteries, the second lottery type (CERT\(_{100}\)) was adapted to include a sure gain in one gamble. To that end, two equal outcomes were displayed in Gamble B. Two outcomes of equal magnitude but varying probabilities of winning effectively added up to a sure gain (i.e., 100%) for Gamble B. The certainty effect thus clearly pointed to Gamble B.
The third lottery type (CERT\textsuperscript{99}) contained an almost certain outcome for one gamble. That is, one outcome’s probability of winning was .98 or .99 in Gamble B. Hence, the (almost) certainty effect pointed to Gamble B. In the fourth type of lottery (ZERO), a zero-outcome was included in Gamble A. While the mean expected values of both lotteries remained very similar or the same, choosing Gamble A posed the risk of gaining nothing at all, i.e., a zero-outcome. The zero effect thus pointed to Gamble B.

The fifth lottery type (CERT\textsubscript{ZERO}) had one zero-outcome as well as one almost certain outcome in Gamble A. Here, the zero effect pointed to Gamble B, but the (almost) certainty effect pointed to Gamble A. Thus, this type of lottery created a conflict between competing motivations: avoiding the zero-outcome of Gamble A and (at the same time) being attracted to the (almost) sure gain of Gamble A.

The lotteries were presented in fully randomized order for every participant. Each lottery followed a blank screen (2000 ms) and fixation cross (1000 ms). The eight pieces of information per lottery (i.e., two outcomes and two probabilities per gamble) were presented in white font framed by a black square (110 × 110 pixels) and had the same distance to the center of the screen. The on-screen position of all gamble attributes was fully randomized in order to counteract habituation effects. Thus, participants could not get used to process probabilities and outcomes in a particular sequence (e.g., probabilities first and outcomes second or vice versa), but were required to stay focused on the task and to actively search for information on the screen. Areas of interest (AOIs) were defined slightly larger than the black frame (179 × 105 pixels per AOI) around each piece of information. Participants indicated their choice (left or right) by pressing one of two buttons on a response pad (Cedrus RB-530) located in between the eye-tracker and the monitor.

After completion of the lottery choice task, participants self-reported on demographic information (age, gender, field of study) and answered three open questions on whether they followed a specific strategy during their lottery choices. Finally, participants were thanked, debriefed, and paid according to their individual earnings in the lottery choice task.

Results
First, lottery choices were analyzed to disentangle the contributions of the certainty effect and the zero effect to decisions under risk. To that end, I tested whether the choice proportions for Gamble A were different from chance (i.e., .50) in the five lottery types and different from each other. Then, decision times, fixations, and saccades were analyzed to check whether zero-outcomes rendered choices easier and quicker to process. The distribution of visual attention across the four outcomes of one lottery was examined to replicate prior findings that zero-outcomes received a smaller share of the overall number of fixations. Finally, a largely explorative analysis of pupil dilation change over time dependent on the lottery type was conducted.

Table 14
Choice proportion means and standard deviations (in parentheses) and results of one-sample t-tests (two-tailed) against the chance value of .50 to choose Gamble A.

<table>
<thead>
<tr>
<th>Lottery type</th>
<th>Mean (SD)</th>
<th>t(34)</th>
<th>p</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIM</td>
<td>.53 (.15)</td>
<td>1.36</td>
<td>.183</td>
<td>0.23</td>
</tr>
<tr>
<td>CERT₁₀₀</td>
<td>.60 (.17)</td>
<td>3.37</td>
<td>.002</td>
<td>0.58</td>
</tr>
<tr>
<td>CERT₉₉</td>
<td>.63 (.22)</td>
<td>3.46</td>
<td>.001</td>
<td>0.59</td>
</tr>
<tr>
<td>ZERO</td>
<td>.15 (.22)</td>
<td>9.18</td>
<td>&lt; .001</td>
<td>1.57</td>
</tr>
<tr>
<td>CERTZERO</td>
<td>.40 (.29)</td>
<td>2.00</td>
<td>.054</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Lottery choices. Choice proportions for all lottery types are displayed in Figure 8. To test the predictions building on the certainty and zero effects regarding the choice proportions for each type of lottery, the probability of choosing Gamble A in each category was tested against the value of .50 (i.e., against chance; five separate two-tailed one-sample t-tests were used), see Table 14 for an overview of the t-test statistics. Choice proportions were not different from chance for SIM lotteries (\(M_{\text{SIM}} = .53, SD = .15\)). Consistent with the predictions on the certainty effect, choice proportions were greater than .5 for CERT₁₀₀ (\(M_{\text{CERT₁₀₀}} = .60, SD = .17\)) and CERT₉₉ (\(M_{\text{CERT₉₉}} = .63, SD = .22\)). In line with the predictions of the zero effect, choice proportions were smaller than .50 for ZERO lotteries (\(M_{\text{ZERO}} = .15, SD = .22\)), and a tendency for CERTZERO lotteries to show choice proportions smaller than .50 (\(M_{\text{CERTZERO}} = .40, SD = .29\)) was observed.
These results replicated the certainty effect and additionally demonstrated a robust zero effect in risky choices.

Figure 8. Probability of choosing Gamble A for each type of lottery. SIM had very similar outcomes overall, no systematic preference for any gamble was predicted. CERT\(_{100}\) had two outcomes of the same value (i.e., one certain outcome) in Gamble A, the certainty effect pointed to Gamble A. CERT\(_{99}\) had an almost certain outcome with a very high probability (.99 or .98) in Gamble A, the (almost) certainty effect pointed to Gamble A. ZERO included a zero-outcome in Gamble A, the zero effect pointed to Gamble B. CERT\(_{ZERO}\) had one zero-outcome and one almost certain outcome in Gamble A, the certainty effect pointed to Gamble A and the zero effect pointed to Gamble B. Error bars indicate standard errors of the mean.

For further analysis, a repeated measures analysis of variance was run on the choice proportions, using the lottery type as a within-subjects factor. The type of lottery determined choices, \(F(3.09, 105.05) = 32.31, p < .001, \eta^2 = .487\). Pairwise comparisons (using Bonferroni correction for multiple comparisons) indicated that the probability of choosing Gamble A was not different for the lottery types SIM, CERT\(_{100}\), and CERT\(_{99}\). This result suggested that the prospect of a sure (CERT\(_{100}\)) or almost sure gain (CERT\(_{99}\)) did not increase choice proportions for that gamble, relative to lotteries that contained
very similar gambles in terms of outcome and probability structure (SIM). This raised some doubts about the strength of the certainty effect. Yet, the latter three lottery types differed from ZERO and CERT\textsubscript{ZERO} lotteries, suggesting that choices for Gamble A were significantly decreased when it contained a zero-outcome, relative to SIM, CERT\textsubscript{100}, and CERT\textsubscript{99}.

**Decision times, fixation count, and saccades.** Mean decision times, fixation count, and number of saccades per decision for all types of lotteries are shown in Table 15. Decision times were log-transformed to reduce skewness. Trials were excluded if the logged decision time was outside of three standard deviations above or below the mean of the logged decision time distribution. This resulted in the exclusion of four trials (0.23% of all trials). To assess the impact of lottery types on decision times, a mixed-effect model analysis on the logged decision time data was performed, entering lotteries and participants as random effects and lottery type as a fixed effect. A likelihood ratio test was used to compare this model to a reduced baseline model (in which only the random effects were entered) in order to assess the impact of the fixed effect of lottery type. All mixed-effect models were fit with R using the \texttt{lmer} function from \texttt{lme4} package (Bates et al., 2015; R Core Team, 2016).

Table 15

<table>
<thead>
<tr>
<th></th>
<th>SIM</th>
<th>CERT\textsubscript{100}</th>
<th>CERT\textsubscript{99}</th>
<th>ZERO</th>
<th>CERT\textsubscript{ZERO}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision time</td>
<td>13.91 (5.31)</td>
<td>12.74 (3.85)</td>
<td>11.80 (4.04)</td>
<td>10.52 (4.75)</td>
<td>9.88 (3.14)</td>
</tr>
<tr>
<td>Number of fixations</td>
<td>46.87 (16.87)</td>
<td>41.46 (11.39)</td>
<td>38.84 (12.32)</td>
<td>34.45 (14.39)</td>
<td>31.64 (9.79)</td>
</tr>
<tr>
<td>Number of transitions</td>
<td>28.94 (10.51)</td>
<td>25.69 (6.90)</td>
<td>24.44 (8.00)</td>
<td>21.43 (8.05)</td>
<td>20.20 (5.98)</td>
</tr>
</tbody>
</table>

The analysis indicated that the type of lottery affected decision times, $\chi^2(4) = 58.69, p < .001$. Relative to the SIM lotteries, decisions were faster in all other lottery types. Specifically, the log decision time was reduced for CERT\textsubscript{100} lotteries by -0.02, .95 confidence interval [-0.06, 0.01]; for CERT\textsubscript{99} by -0.06 [-0.09, -0.02]; for ZERO by -0.13 [-0.16, -0.10]; and for CERT\textsubscript{ZERO} by -0.15 [-0.19, -0.12]. Hence, decisions
were slowest for SIM and CERT\textsubscript{100} lotteries and fastest for ZERO and CERT\textsubscript{ZERO} lotteries, suggesting that zero-outcomes led to expedited choices. This finding was consistent with the prediction that decisions would be faster for zero-outcome lotteries.

The number of fixations per decision was analyzed using the same procedure. Note that decision times, the number of fixations, and the number of transitions are inherently collinear and that these measures (and thus, the analyses) cannot be considered independent. As expected, difficult lotteries with high similarity of probabilities and outcomes (SIM) generated the most fixations (and the slowest decisions) while lotteries that included a zero-outcome (ZERO, CERT\textsubscript{ZERO}) required less fixations. Analogous to the decision time analysis, the lottery type affected the number of fixations, $\chi^2(4) = 49.29$, $p < .001$. Compared to the SIM lotteries, all other lottery types yielded less fixations. In more detail, the number of fixations per decision was reduced in CERT\textsubscript{100} lotteries by -5.42 [-9.01, -1.83]; in CERT\textsubscript{99} by -8.03 [-11.62, -4.44]; in ZERO by -12.43 [-16.02, -8.84]; and in CERT\textsubscript{ZERO} by -15.26 [-18.82, -11.64].

Finally, eye movements (saccades) were coded as transitions if they occurred from one AOI to another, i.e., from one gamble attribute to another. Hence, all saccades from or to the fixation cross or any other point of interest outside the pre-defined AOIs were omitted. This included the first saccade of every trial, which was typically a saccade from the fixation cross (displayed in the center of the screen) to one of the gamble attributes.

Again, a mixed-effect model analysis was performed to analyze the transitions, entering lotteries and participants as random effects and lottery type as fixed effect. This model was compared to the baseline model (only random effects) to assess the impact of the fixed effect of lottery type. Similar to the decision time and fixation analyses, the number of transitions was affected by lottery type, $\chi^2(4) = 45.77$, $p < .001$. Compared to the SIM lotteries, all other lottery types elicited fewer transitions. In more detail, the number of transitions per decision was reduced in CERT\textsubscript{100} lotteries by -3.25 [-5.47, -1.03]; in CERT\textsubscript{99} by -4.50 [-6.72, -2.28]; in ZERO by -7.51 [-9.73, -5.29]; and in CERT\textsubscript{ZERO} by -8.74 [-10.96, -6.52]. Thus, in line with the predictions, the number of transitions was smallest when lotteries included a zero-outcome (ZERO and CERT\textsubscript{ZERO}) and largest for difficult lotteries with similar outcomes and probabilities (SIM). This finding supported the interpretation that zero-outcomes did not have to be integrated with
their probabilities in order to calculate expected utilities, because their utility is zero. Therefore, they were processed more easily than non-zero outcomes. When included in a lottery, zero-outcomes reduced the information load and represented largely negligible gamble attributes. For this reason, they simplified the decisions. It should be noted, though, that this finding was also consistent with the zero effect perspective because fewer saccades to zero-outcomes would also be expected in the case of motivated avoidance.

Attention to gamble attributes. To further examine whether the reduction of fixations and transitions in the presence of zero-outcomes could be attributed to the existence of zero-outcomes, I compared the fraction of fixations that were directed at the four outcomes of one lottery. If the reduction of the overall number of fixations in the lotteries that included a zero-outcome could be traced back to the latter, it should be observable that zero-outcomes were generally less fixated than other outcomes simultaneously displayed. This effect has been reported in prior research and it would be expected if zero-outcomes attracted less attention because this information was processed easily and rather effortlessly, either because zero-outcomes did not require the processing of respective probabilities, or due to the motivated avoidance of these outcomes. The well-established effect of reduced attention to zero-outcomes (e.g., Glöckner & Herbold, 2011; Pachur et al., 2018) was replicated. Five mixed-effect models on the fraction of fixations confirmed this effect. These models were fit separately for the five lottery types, entering lotteries and participants as random effects and outcome (A1, A2, B1, B2) as a fixed effect.

Figure 9 shows the distribution of fixations across the four outcomes for all lottery types except for SIM lotteries. For the SIM lotteries, fixations were about equally distributed to the four outcomes, i.e., the same share of approximately 25% of all fixations to outcomes were directed at each of the four outcomes. This validated the assumption that these lotteries were difficult as their attributes were in fact judged as quite similar since no single one of the four outcomes attracted relatively more attention than the other ones. Thus, as expected, the fixed effect of outcome was not significant for SIM lotteries, $\chi^2(3) = 5.13, p = .163$. 
Figure 9. Fraction of fixations directed at the four outcomes of one lottery (Gamble A: A1, A2; Gamble B: B1, B2) across four different lottery types. CERT$^{100}$ had two outcomes of the same value in Gamble A, outcome B2 was the highest achievable outcome. CERT$^{99}$ had in Gamble A an almost certain outcome with very high probability (.99 or .98; outcome A1) and an outcome with very low probability (.01 or .02; outcome A2). ZERO included a zero-outcome in Gamble A (outcome A2). CERTZERO had a zero-outcome (outcome A2) an almost certain outcome (.99 or .98, outcome A1) in Gamble A. Error bars indicate SEM. The dotted line denotes equal distribution of fixations to outcomes, i.e., 25% directed at each outcome.

However, significant deviations from the equal distribution of fixations to all outcomes were observed in the other four lottery types. Most notably, when a zero-outcome was included in a lottery, substantially less fixations were directed at this outcome. The fixed effect of outcome affected the fraction of fixations in ZERO lotteries, $\chi^2(3) = 100.23$, $p < .001$. Compared to A1 outcomes in these lotteries, which received 27.94% of the overall attention to outcomes, the fraction of attention to zero-outcomes (A2) was reduced by -8.12 [-9.86, -6.38] percentage points (see Appendix, Table C2 for a complete report of all model estimates). A very similar, somewhat more pronounced pattern was found in CERTZERO lotteries, $\chi^2(3) = 206.84$, $p < .001$. Here, A1 outcomes
received 28.85% percent of the overall attention to outcomes, and this was reduced for zero-outcomes (A2) by -11.88 [-13.63, -10.14] percentage points.

It is noteworthy that fixations were also unequally distributed to the four outcomes of the CERT\textsubscript{100} and CERT\textsubscript{99} lotteries, however, to a much lesser extent. In the CERT\textsubscript{100} lotteries, the fraction was affected by outcomes, $\chi^2(3) = 21.72, p < .001$, such that the B2 outcomes received 3.22 [1.69, 4.75] percentage points more fixations than A1 outcomes (complete model report shown in Table 2A, Appendix). In these lotteries, B2 outcomes were (mostly) the outcomes with the highest absolute value. In CERT\textsubscript{99} lotteries, the fraction was also affected by outcomes, $\chi^2(3) = 62.41, p < .001$. Here, the outcomes with very high probabilities (.98 or .99; A1) received a larger portion of the overall fixations on outcomes, i.e., 28.05 [27.03, 29.07] percentage points, while the outcomes with very small probabilities (.01 or .02; A2) were relatively less fixated by -5.84 [-7.29, -4.40] percentage points. These findings indicated that high absolute outcomes drew relatively more attention than other outcomes (in CERT\textsubscript{100} lotteries), and that this was also true for high probabilities of .98 or .99 (in CERT\textsubscript{99} lotteries), while very low probabilities of .02 or .01 drew relatively less attention.

**Pupil dilation.** To explore pupillary responses to lotteries dependent on the lottery types, only the first 3000 ms of each trial were analyzed. Only trials in which decisions took at least 3000 ms were taken into consideration, resulting in the exclusion of 22 trials (1.26% of all trials). Each trial was divided into 30 bins of 100 ms and the percentage of pupil size change relative to a pre-stimulus baseline was computed (see, e.g., Cavanagh et al., 2014; Fiedler & Glöckner, 2012). The baseline pupil size was determined per trial as the median pupil dilation during 500 ms before the lotteries appeared on the screen (each lottery was preceded by a fixation cross). The mean percentage of pupil dilation change during the first three seconds of each trial, dependent on lottery types, is displayed in Figure 10. Visual inspection of the pupillary response suggested that it developed similarly over time until approximately 1000 ms but differed notably afterwards. This lag in pupillary response to an eliciting stimulus was typical because pupil dilation is generally slow; the findings were comparable to earlier work (e.g., Cavanagh et al., 2014; Kinner et al., 2017; van Steenbergen & Band, 2013).
Figure 10. Percentage of change in pupil size over time, relative to the pre-stimulus baseline, depending on the type of lottery. SIM had very similar outcomes, CERT$_{100}$ had two outcomes of the same value (i.e., one certain outcome), CERT$_{99}$ had an almost certain outcome, ZERO included a zero-outcome, and CERT$_{ZERO}$ had both a zero-outcome and an almost certain outcome.

To assess whether the type of lottery affected pupil size change, mixed-effect model analyses were performed for each bin, entering lotteries and participants as random effects and lottery type as fixed effect. Prior work demonstrated that pupil size changed as a function of the lotteries’ mean expected value (Fiedler & Glöckner, 2012; see also Experiment 2). Therefore, the mean expected value was added as an additional fixed effect. As expected, the mean expected value of lotteries affected the pupil size change between bins 15 to 29 (i.e., between 1500 ms and 2900 ms). The bin-wise comparison of the model including the fixed effect of lottery type to a reduced model (only random effects and the fixed effect of mean expected value) indicated that the type of lottery affected pupil size change from bins 14 through 21 (i.e., between 1400 ms and 2100 ms) but neither before nor after that period of time.
For example, in bin 18 (i.e., at 1800 ms after the stimulus onset), in which the biggest differences based on lottery types were observed, the mean expected value was a significant predictor of pupil size change, $\chi^2(1) = 5.76, p = .016$, increasing pupil size by 0.02 [0.00, 0.03] percentage points. Lottery type affected the pupil size change, $\chi^2(4) = 15.40, p = .004$. Compared to the SIM lotteries, all other lottery types evoked greater changes in pupil dilation; CERT\textsubscript{100} lotteries increased pupil size by 0.55 [-0.21, 1.31]; CERT\textsubscript{99} by 1.48 [0.69, 2.27]; ZERO by 0.89 [0.08, 1.68]; and CERT\textsubscript{ZERO} by 1.22 [0.41, 2.02] percentage points. This finding further supported the idea that pupil dilation tracked during economic decisions reflected arousal (independently from the valence of an outcome) rather than cognitive effort. If cognitive effort were to impact pupillary response (more than affect), greater changes in pupil dilation would be observed for SIM lotteries compared to other lottery types. This would be expected because these lotteries were deemed the most difficult ones (as indicated by slower decisions, higher numbers of fixations, and fewer transitions). In contrast, pupils dilated more in response to easier lotteries in general, and most to the easiest type of lotteries (CERT\textsubscript{ZERO}) in particular.

This finding added an important aspect to the explanation that zero-outcomes were neglected simply because their utility was zero (independent of their probability; see above). Assuming that changes in pupil dilation reflected affective responses rather than effort, the results implied that zero-outcome lotteries (but also lotteries with sure gains) increased arousal relative to SIM lotteries. This would not be expected if zero-outcomes received less attention simply because they were easier to process than non-zero outcomes. Though, this finding was consistent with the notion that zero-outcomes elicit negative affect and avoidance motivation. Hence, there was initial evidence for the role of affect in modulating the attentional response to zero-outcomes. Notably, the changes in pupil size were even greater for CERT\textsubscript{ZERO} lotteries, an additional interesting finding I will turn to in the Discussion section.

**Discussion**

Experiment 3 demonstrated a robust zero effect in decisions under risk, indicating that decision makers confronted with (more or less) risky gambles were motivated to avoid zero-outcomes. The findings supported the view that zero-outcome avoidance was
based on automatic processes to avoid these outcomes immediately and that this was associated with (negative) affect. Consequently, decision makers were more likely to opt for the option with a gain greater than zero if available (ZERO lotteries). If a zero-outcome was combined with an almost sure gain (CERT\textsubscript{ZERO} lotteries), decision makers preferred avoiding the zero-outcome over choosing the (almost) sure lottery gain. They did so quicker than in difficult trials in which the lottery attributes were quite similar, and they allocated less visual attention to lotteries overall in the presence of zero-outcomes. This observation indicated decreased decision difficulty for lotteries with zero-outcomes, replicating earlier work (Glöckner & Herbold, 2011; see also Experiment 2). Participants also made only very few transitions to zero-outcomes, consistent with previous research (Franco-Watkins & Johnson, 2011). This finding indicated fewer expected utility computations in the case of zero-outcomes (in fact, expected utility computations should be very rare in the case of zero-outcomes). This was in line with the explanation that zero-outcomes were essentially ignored in terms of visual attention since they did not require the integration of the respective probabilities. However, the pupil dilation analysis added important insights to the eye movement data. The pupil data supported the view that zero-outcomes elicited a strong (negative) affective response that would not be expected under the explanation that zero-outcomes were attentionally disregarded simply because they were not meaningful for expected utility evaluations. That is, the findings from Experiment 3 supported the latter explanation but stressed that there may be more to the processing of zero outcome information than just that rather simple explanation.

The analysis of choice proportions revealed mixed evidence regarding the question of whether the certainty effect or the zero effect dominated risky choices, in particular when pitted against each other. First, one-sample $t$-tests against the chance probability of choosing Gamble A (i.e., a choice proportion of .50) indicated that decision makers preferred certain or almost certain outcomes if available. Choice proportions were significantly greater than .50 for CERT\textsubscript{100} and CERT\textsubscript{99} lotteries. Based on this analysis, it could be concluded that the certainty effect influenced choices, as conventionally predicted. However, when running a repeated measures analysis of variance on the choice data, pairwise comparisons indicated that choice proportions in the latter two lottery types were not different from SIM lotteries, which in turn had a choice proportion for Gamble A not different from .50. This analysis supported the competing prediction based on the
preliminary findings of the working paper by Incekara-Hafalir and Stecher (2016), challenging the predictive validity of the certainty effect and suggesting that decision makers were not primarily attracted to sure gains, as usually assumed.

Independent from the analytical approach, the zero effect consistently predicted choice proportions. Decision makers avoided receiving zero-outcomes. When pitted against almost sure gains, zero-outcome avoidance still reduced choice proportions significantly, but to a much lesser extent. This finding suggested that decision makers were attracted to almost sure gains (when these were combined with zero-outcomes), but their motivation to avoid receiving zero-outcomes seemed to outweigh their attraction to sure gains.

Several conclusions may be drawn from these analyses. First, the zero effect in risky choices was robust across variations of other gamble attributes (such as the probability of winning non-zero outcomes), but it varied in magnitude depending on the type of lottery. Second, the certainty effect seemed to influence choice proportions to a greater extent when interacting with zero-outcomes. That is, the influence of (almost) sure gains was most notable when directly comparing the ZERO and CERTZERO lottery types, i.e., when directly comparing zero-outcomes with almost sure gains. The evidence for the certainty effect as a strong determinant of decisions by itself, that is, without the support of other features of the decision environment, was rather weak. Providing sure gains resulted in choice proportions different from chance, but not different from a reference (baseline) decision task category (i.e., SIM lotteries). Only if sure gains in one gamble were contrasted with zero-outcomes in the other gamble (as in the decision task by Kahneman & Tversky, 1979) did the certainty effect appear to bias choices toward the sure option.

8 There was further anecdotal evidence in support of this claim. After completion of the lottery choice task, decision makers responded to an open question regarding their use of specific strategies for choosing between the gambles. These responses were categorized in terms of whether they referenced the certainty effect (i.e., a preference for sure gains) or the zero effect (avoidance of zero-outcomes). Out of ten participants who indicated using a specific strategy, only one specified a preference for sure gains, but nine declared having generally avoided choosing the zero gain option. Thus, when reflecting upon their decision strategies, the participants appeared to be quite aware of the zero effect.
Third and finally, when directly comparing the certainty effect and the zero effect (by combining both almost sure gains and zero-outcomes within one gamble; CERTZERO lotteries), the latter might have had greater impact on choices than the former. I supposed that the zero effect could be stronger than the certainty effect based on the findings from CERTZERO lotteries, in which the effects were pitted against each other. If both decision biases were equally effective, their influence on choice proportions should cancel out one another on average. But a reduction of choice proportions in CERTZERO lotteries was observed, suggesting that the zero effect had a somewhat stronger impact than the certainty effect. Note that caution is advised regarding this claim, given the need for further replication of the effects in question. Future research should consolidate the evidence in support of the zero effect in decisions under risk and further clarify the overlap or potential interaction with the certainty effect.

Pupillary responses differed between the lottery types. Notably, pupil size change over time did not (exclusively) reflect differences in decision difficulty (Kahneman & Beatty, 1966) or mean expected value (Fiedler & Glöckner, 2012), but appeared to reflect mainly hedonic lottery features. This finding suggested that pupil dilation signaled arousal rather than effort in risky choices. Hence, these findings contributed to the ongoing debate in decision research and psychophysiology (e.g., Kinner et al., 2017) on the determinants of stimulus elicited pupil dilation changes over time.

Zero-outcomes (ZERO, CERTZERO), and also almost sure gains (CERT99), triggered greater changes in pupil dilation than difficult SIM lotteries. This finding had two important implications. First, it suggested that pupillary responses reflected affective arousal rather than cognitive effort. Difficult lotteries, which can be expected to require the greatest amount of effort in order to be processed before making choices (indicated

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9 To enhance the confidence in this finding, I re-analyzed data available online (at https://osf.io/em8h6) from Fiedler and Glöckner (2012). In Experiment 1 of this article, a lottery choice task similar to the one in Experiment 3 was used. It included zero-outcome lotteries and rather difficult lotteries similar to the category SIM. Modeling pupil size change over the first 15 fixations of each trial, greater changes for zero-outcome lotteries were observed relative to SIM, $b_{\text{zero}} = 0.557 [0.062, 1.176]$, the effect was marginally significant, $\chi^2(2) = 2.92, p = .088$. As reported by Fiedler and Glöckner (2012), the mean expected value did not affect pupil dilation in this study.
by the slow decisions in these lotteries), consistently triggered smaller changes in pupil dilation than all other lottery types. The processing of difficult decisions required extended information search (indicated by more fixations, compared to the other lottery types) and the comprehensive integration of all available information. Thus, it required increased cognitive effort in order to determine the best option in terms of expected utility. Hence, the observed smaller changes in pupil size for these difficult lotteries compared to the other four lottery types strongly suggested that pupil dilations reflected arousal rather than effort during decisions under risk. In line with this assumption, it could also be argued that SIM lotteries were generally less attractive to the decision makers than the other four lottery types because it was rather difficult to determine what would be the best option. In other words, SIM lotteries could evoke less arousal than other lotteries simply because they were less appealing overall.

Second, the notion that almost certain gambles elicited even greater changes in pupil dilation than ZERO and CERTZERO lotteries emphasized that pupillary responses were affected by multiple sources of arousal. The nature of the CERT0.99 lotteries could explain why they would trigger the greatest changes in pupil size. While including slightly more uncertainty than, for instance, sure gains (i.e., by including an almost sure gain with 0.98 or 0.99 probability), these lotteries might have particularly stimulated gambling behavior and could therefore have raised arousal in terms of (positive) excitement. Both uncertainty (see Urai et al., 2017) and excitement, which should be accompanied by an increase in state arousal, could be reflected in the pupillary response. It is important to note that the pupillary response presumably reflected much more than the affective reactions triggered by zero-outcomes or comparably high mean expected values of lotteries (Fiedler & Glöckner, 2012). The findings from Experiment 3 indicated that inducing uncertainty, by even as little as reducing the probability of lottery gains from certainty to 0.99 or 0.98, had a considerable impact on pupil dilation.

In addition, it might well be that the excitement of an almost sure gain evoked stronger positive affect than the negative response elicited by zero-outcomes. This highlights another important aspect. While the results of Experiment 3 strongly suggested that pupillometry can be used to unobtrusively trace arousal during decision making, changes in pupil size do not indicate the current affective states’ valence (see also Bradley, Miccoli, Escrig, & Lang, 2008). As is the case with the P300 in EEG research,
the valence of the affective response signaled by the pupil must be concluded from the experimental stimulus. In the present study, the different lottery types could elicit distinctly valent affective responses. Zero-outcomes are certainly unpleasant in the gain domain (this might be quite different in the loss domain), but almost sure gains might be suited to induce an enjoyable sensation linked to gambling and reflect a high expectation of reward. Future research should consider the potential contributions of distinct sources of affective response to pupillary responses in general, and pupil dilation change in decisions under risk in particular.

Differences in mean expected values were also reflected in pupillary response (see also Fiedler & Glöckner, 2012, Study 2). While the average mean expected values were very similar and comparable for three lottery types in the present experiment (roughly 35E in CERT$^{99}$, ZERO, CERT$^{ZERO}$), two other lottery types had considerably larger average mean expected values (about plus 50E in SIM and CERT$^{100}$). It was surprising that the latter two lottery types triggered the smallest changes in pupil dilation in the present experiment, given the finding of Fiedler and Glöckner (2012) that pupils dilated as a function of mean expected value. Based on the data from Experiment 3, I argued that the affective response to excitement over almost sure gains or disappointment about zero-outcomes was larger than the differences in pupil dilation change elicited by distinct mean expected values. There was some initial support for this idea in the present pupillometry data, but the evidence remained inconclusive due to the variation of the base-rate mean expected values in the different lottery types. Future research should address this issue to further disentangle the contributions of mean expected values and affective responses to pupil dilation in decisions under risk.

The findings from Experiment 3 highlighted that affect may play an important role in processing zero-outcome information in decisions under risk. I argue that outcomes of zero value evoked an affective response which facilitated the processing of lottery information rather effortlessly (for a similar argument, see Bateman et al., 2007; Finucane et al., 2000; Shampanier et al., 2007). Earlier work on the zero effect in pricing suggested that free products were not only assessed in terms of their reduced costs but that zero prices also seemed to add to the perceived benefits of these products (Shampanier et al., 2007; Votinov et al., 2016). In this sense, the zero-price effect described by Shampanier et al. (2007) could be considered the equivalent of the zero effect described in the present
dissertation, but in the loss domain. Similar to the earlier work on the zero-price effect, I concluded that zero-outcomes in risky choices not only triggered reactions that could be expected for outcomes of no expected value, but that they were interpreted like losses (just like zero prices were considered gains).

It can be safely assumed that this is the case in the experimental setup used in this study, in which all other outcomes were gains. As such, it was imperative for the decision maker to avoid them since every alternative outcome would be more interesting in this gains-oriented environment. The results from the decision time analysis further supported this assumption. Decision times were comparably low in lotteries that included zero-outcomes, as well as the number of fixations on these outcomes. Hence, decision makers allocated relatively less attentional resources to zero-outcomes than to other outcomes, appearing to avoid gathering additional adverse information, perhaps in order to keep the psychological impact of these rather disappointing outcomes as low as possible (Galai & Sade, 2006; Karlsson et al., 2009).

An alternative explanation for why zero-outcomes were disregarded in terms of visual attention could be founded on the concepts of self-control and emotion regulation (e.g., Gross, 1998; Hügelschäfer & Achtziger, 2017). Conceivably, decision makers could actively seek to avoid zero-outcomes in order to minimize their negative impact on the affective state. The active avoidance of specific information, and thus, the controlled inhibition of automatic attention processes (such as allocating visual attention to all available information), however, would require self-control and can be considered rather effortful. Hence, when zero-outcomes were actively avoided, one would expect lottery choices to be slower and more cognitively demanding if zero-outcomes were present (relative to other lotteries without zero-outcomes), because increased cognitive effort would be required to inhibit automatic attention processes. The data from Experiment 3 did not support this idea. Instead, the results indicated that risky choices were faster and less cognitively demanding when zero-outcomes were included. Based on this evidence, it was more likely that zero-outcome avoidance relied on automatic processing rather than effortful self-control.

Taken together, the present experiment suggested that processing information about zero-outcomes was quick, rather effortless, without conscious intent, and thus
fulfilled the criteria of automatic decision processes (W. Schneider & Shiffrin, 1977; Strack & Deutsch, 2004). In this sense, zero-outcomes cued automatic decision processes. They triggered the immediate attentional avoidance of options that included this outcome, without deliberation, without effort, and without conscious intent.

One limitation of Experiment 3 was that lottery choices were restricted to the domain of gains. It would be particularly interesting to run a comparable experiment using lotteries from the loss domain, or one step further, to use mixed-domain lotteries. If all other outcomes in a lottery were losses, it would be expected that zero-outcomes have positive valence, i.e., they should be more attractive and have much higher utility than any other outcome, since they entail not losing any money. If zero-outcomes in the loss domain were judged similarly to gains in the gain domain, this would further support the extraordinary exceptional nature of this number in processing information about risky choices. Future research should consider this opportunity to clarify this issue.

The results also provided implications for theoretical advancement in decision research. Recently, the role of visual attention was integrated in theories of risky choice, and economic decision making more generally (Bordalo et al., 2012; Krajbich et al., 2010; S. M. Smith & Krajbich, 2019; Tavares et al., 2017). It could be particularly insightful to engage in model comparisons by deriving specific predictions about how attention should or should not be allocated to zero-outcomes under specific circumstances such as the features of the decision environment. Given the extraordinary nature of this number, and its unique unambiguousness, it might be worthwhile considering its exceptionality when specifying models of decisions under risk.
CHAPTER 8
GENERAL DISCUSSION

In the scope of the present dissertation, four experiments examined the role of motivation and volition in economic decisions. The main objective was to investigate how experimentally induced motivational and volitional states of mind, the deliberative and implemental mindsets as defined by the mindset theory of action phases, would influence economic decisions and their processes, and how these influences were modulated by financial incentives. Across four experiments, different methods and decision making paradigms were deployed. The interactive effects of mindsets and incentives on economic decisions were scrutinized in Experiments 1a and 1b, using a classic decision task from the heuristics and biases literature. Moving on to the level of processes, Experiment 2 examined the effects of the deliberative and implemental mindsets on decision processes under risk by means of eye tracking. Experiment 3 then followed up on a surprising observation made in the previous experiment, taking a closer look at how particular attributes of the decision environment shape affective and motivational processes in the risky choice paradigm. Taken together, these studies produced interesting, novel insights regarding the role of motivation and volition in economic decisions, yielding a number of important implications for empirical research in decision science, motivation research, and beyond.

In a nutshell, the findings of the present dissertation can be summarized in terms of four main conclusions. First, it was shown that financial incentives were effective for improving economic performance when the payment of attractive monetary rewards was contingent on the performance in the decision task, compared with a fixed rate payment regardless of the decision makers’ performance. Yet, higher performance-based incentives did not further improve economic decisions relative to lower performance-based payments. Hence, consistent with prior meta-analytic work on this issue (Cerasoli et al., 2014), the importance of financial incentives for determining economic decisions
is best defined in terms of the incentive salience, i.e., the degree to which financial incentives are directly tied to the performance in a given task, rather than the absolute amount of incentivization.

Second, the deliberative and implemental mindsets did not directly affect economic decisions. This was true for both the classic heuristics and biases decision task and the lottery choice task. That is, there was converging evidence from these different paradigms which supported the conclusion that the deliberative and implemental mindsets did not directly influence economic decisions in these tasks. Hence, this conclusion could be drawn with some confidence. On a side note, the finding that mindsets did not determine performance in base-rate neglect and conjunction fallacy problems (see Experiments 1a, 1b) was also consistent with the results from a study related to the aims of the present dissertation. Ludwig, Ahrens, and Achtziger (in press), investigating response times in a probability judgment task, also included an experimental manipulation of mindsets in order to explore the effects of motivation and volition on decision times in this paradigm. Consistent with the findings from the experiments reported here, there were no effects of the deliberative and implemental mindsets on error rates and decision times in the probability judgment task. It should be noted, though, that prior research had discovered deliberative and implemental mindset effects on economic decisions, in the laboratory and in the field, using yet different choice paradigms (e.g., Griffith et al., 2015; Li et al., 2019). As discussed above, it remains a challenge for future research to identify the critical decision environments in which motivational and volitional processes may directly affect economic performance.

Third, mindsets interacted with financial incentives in determining economic performance and decision processes. Even though there was no direct effect of mindsets on performance, initial evidence from both, the heuristics and biases task and the lottery choice paradigm, suggested interactive effects of mindsets and incentives. Specifically, it appeared that the effects of the deliberative and implemental mindsets on decisions and their processes became apparent as predicted only when decisions were incentivized. That is, the present dissertation presented the novel finding that the influence of motivational and volitional processes on economic decisions, and their processes, depended on the appropriate incentivization of the experimental task at hand. In other words, mindsets were relevant predictors of economic decision outcomes and processes only if the
decision task was attractive for the decision makers in terms of their individual earnings. This finding was particularly interesting given that some previous studies on the deliberative and implemental mindsets did not incentivize choices (e.g., Rahn et al., 2016b). Potentially, the lack of incentivization could have biased the results and the conclusions drawn from them. In the case of the lottery choice paradigm, the direct comparison of two studies that did not differ in terms of the experimental protocol in any other aspect than the incentive mechanism (i.e., Rahn et al., 2016b and Experiment 2 of the present dissertation) implied a fundamental importance of financial incentives in determining how mindsets would affect decision processes in the lottery choice task. In light of this finding, it is important to emphasize the necessity to provide appropriate incentives in order to elicit the cognitive processes that characterize the deliberative and implemental mindsets.

Fourth and finally, affective and motivational processes beyond those instigated by the deliberative and implemental mindsets played a key role in decisions under risk. Particular decision attributes seemed to trigger specific affective and motivational processes which then translated into considerable attentional and behavioral choice biases. Specifically, zero-outcomes, i.e., lottery outcomes with the value zero, appeared to elicit high levels of arousal and a pronounced motivational tendency of avoidance, as indicated by comparatively greater changes in pupil size (arousal) and relatively less visual attention deployed to these outcomes (avoidance). This interesting, novel finding further corroborated the idea of a zero effect in risky choices (Incekara-Hafalir & Stecher, 2016) and contributed to the ongoing debate in decision research about the psychological antecedents of expected utility theory violations in decisions under risk. Moreover, this finding also informed to the current debate in psychophysiology regarding the relative contributions of cognitive effort and affective arousal to pupil size changes over time (e.g., Kinner et al., 2017).

These four overarching conclusions were based on the results of the tests of several hypotheses about the direct and joint effects of motivational and volitional processes on economic decisions. A summery and overview of these hypotheses and the results in terms of whether they were supported by the data is given in Table 16. As mentioned, there was robust evidence for the idea that incentivizing economic decisions would improve performance (H1) by boosting the effort decision makers were willing to
invest in the decision task (H2), as evidenced by Experiment 1a. Yet, Experiment 1b revealed that the relation among incentive, effort, and performance was not straightforward in the sense that increasing the absolute amount of incentives would linearly translate into greater effort, and thus, improved performance. Higher incentives did not improve performance (H3) and neither was there any evidence for increased effort when performance-based incentives were raised (H4).

The hypotheses that the deliberative mindset would lead to improved performance (H5), while the implemental mindset should impair economic performance (H8), were also rejected based on the findings from Experiments 1a, 1b, and 2. Even though there was no evidence for such main effects of the mindsets on economic decisions, the evidence from Experiment 1a and Experiment 2 supported the idea of interactive effects of the deliberative and implemental mindsets in determining economic decisions and their processes (H11). In more detail, Experiment 1a, and in alleviated terms also Experiment 2, provided initial evidence for the idea that the potential benefits of the deliberative mindset for improving economic performance, through its effects on the breadth of attention and the scrutiny with which incoming information is evaluated, may rely on the proper incentivization of the task at hand. That is, effects of the deliberative mindset on economic decisions may be contingent on the task being sufficiently attractive, so it would be worthwhile for the decision maker to mobilize additional resources that are required to facilitate a greater attentional span and receptivity to all kind of information.

There was also some evidence for a similar explanation of the implemental mindset’s effects on decision processes. Experiment 1a showed that only when the task was attractive in terms of the possible earnings, the implemental mindset expedited choices. This could be explained by a greater reliance on decision heuristics, and thus, a greater susceptibility to decision biases. While the initial prediction was that this would occur for the implemental mindset regardless of whether the task was incentivized or not, Experiment 1a revealed that this detrimental effect of the implemental mindset on economic performance, similarly to the beneficial deliberative mindset effect, may rely on the appropriate incentivization of the experimental task. Note, however, that (at least in Experiments 1a and 1b), faster choices in the implemental mindset, presumably due to increased reliance on decision heuristics, did not mean that performance was impaired.
In this sense, one could also argue that the implemental mindset rendered decision making more efficient, since less effort (as indicated by faster decisions) led to similar performance in terms of correct responses in the decision task.

Robust evidence was provided by Experiment 2 for the predicted effects of the deliberative and implemental mindsets on decision processes under risk. As expected, the deliberative mindset led to more comprehensive information search prior to making a decision (H7), while the implemental mindset was associated with a comparatively greater focus on feasibility-related information (H10). These findings strengthened the argument that motivational and volitional processes determined economic decision processes, even though they did not affect choices in the lottery choice task. In addition, this finding confirmed the idea that the implemental mindset’s cognitive tuning toward mindset-congruent information (i.e., implementation-related information) can be generalized to feasibility-related information.

The evidence from Experiments 1a, 1b, and 2 emphasized the necessity to integrate motivational and volitional processes into formal choice models (see also, e.g., Wedell, 2015). In doing so, one should also take into consideration the recent surge in formal choice models that account for the role of attention in guiding decisions (e.g., Bordalo et al., 2012; Krajbich et al., 2010; S. M. Smith & Krajbich, 2019; see also P. L. Smith & Ratcliff, 2009). From this perspective, a good candidate model built on which the influences of motivational and volitional processes could be incorporated, is the attentional drift diffusion model (aDDM; Krajbich et al., 2010, 2012; Krajbich & Rangel, 2011; Tavares et al., 2017).
Table 16
Overview of the hypotheses and results in Experiments 1a, 1b, and 2.

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<th>Predictions</th>
<th>Exp. 1a</th>
<th>Exp. 1b</th>
<th>Exp. 2</th>
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<td><strong>Incentives</strong></td>
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<td>H1 Performance-based financial incentives improve performance in an economic decision task, compared with a fixed rate payment.</td>
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<tr>
<td>H2 Performance-based financial incentives increase response times in an economic decision task, compared with a fixed rate payment.</td>
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<tr>
<td>H3 High financial incentives improve performance in an economic decision task, compared with low incentives.</td>
<td>✗</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H4 High financial incentives increase response times in an economic decision task, compared with low incentives.</td>
<td>✗</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Deliberative mindset</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H5 The deliberative mindset, relative to a control condition, improves performance in an economic decision task.</td>
<td>✗ ✗ ✗</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H6 The deliberative mindset, relative to a control condition, increases response times in an economic decision task.</td>
<td>✗ ✗ ✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H7 The deliberative mindset, relative to a control condition, increases information search in an economic decision task.</td>
<td>✗</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td><strong>Implemental mindset</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H8 The implemental mindset, relative to a control condition, impairs performance in an economic decision task.</td>
<td>✗ ✗ ✗</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H9 The implemental mindset, relative to a control condition, decreases response times in an economic decision task.</td>
<td>✗ ✗ ✗</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H10 The implemental mindset, relative to a control condition, increases the processing of feasibility-related information in an economic decision task.</td>
<td>✗</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td><strong>Incentive × mindset</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H11 a) Economic performance suffers more from an implemental mindset when choices are incentivized.</td>
<td>✗ ✗ ✗</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b) The beneficial effects of the deliberative mindset for economic performance rely on incentivization.</td>
<td>✓ ✗ ✓</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* ✓ indicates support for the hypothesis, ✗ denotes that the hypothesis was rejected.
As briefly discussed above, the aDDM models decision processes as mathematical diffusion processes of evidence accumulation, giving a central role to visual attention by positing that the process of value integration relies heavily on which information is currently being fixated (see also Krajbich et al., 2010; S. M. Smith & Krajbich, 2019). The aDDM is part of the broader family of sequential sampling models. Sequential sampling models such as the standard drift diffusion model (e.g., Ratcliff, 1978; Ratcliff & McKoon, 2008; Voss, Nagler, & Lerche, 2013) provide a good description of choice patterns and reaction times in different decision making paradigms, including perceptual choice, value-based choice, and confidence judgments in recognition memory tasks (see Forstmann, Ratcliff, & Wagenmakers, 2016; Ratcliff, Smith, Brown, & McKoon, 2016, for an overview).

The standard drift diffusion model includes a number of parameters to describe the decision process of (noisily) accumulating evidence for the available choice options. The four most important parameters are the drift rate, threshold separation, relative starting point, and non-decision time (see, e.g., Voss et al., 2013, for a more elaborate description of the key parameters of the standard drift diffusion model and for more information on other relevant parameters). The drift rate represents the average speed and direction of evidence accumulation. Threshold separation refers to the amount of information that needs to be accumulated before making a choice. The relative starting point reflects an a priori bias (or preference) in decision making. Finally, the non-decision time parameter captures the average duration of peripheral processes like encoding or response execution.

The aDDM overcomes an important limitation of the standard drift diffusion model, namely that attentional processes and their influences on behavioral decisions were not represented in the standard model. It achieves this by introducing an attentional parameter which “discounts the value of the item not looked at by a fraction of this item’s value” (S. M. Smith & Krajbich, 2019, p. 120; see also Krajbich et al., 2010). Thereby, visual attention modulates the process of value integration, i.e., the drift rate. Note that this model posits an interactive effect of attention and value on choice because attention to choice options of higher value was assumed to have a greater effect on choices than attention to low-value options. While this multiplicative model recently received support from several lines of studies (e.g., S. M. Smith & Krajbich, 2019; Tavares et al., 2017), a
different approach suggested that the effect of attention on choice was additive, rather than multiplicative (Cavanagh et al., 2014).

By adding an attentional parameter which determines the drift rate, the aDDM incorporates visual attention as a key component of the decision making process. Yet, the aDDM does not account for what appear to be systematic influences of motivation and volition on attentional processes in value-based choices, i.e., risky choices as reported in Experiment 2 of the present dissertation. These influences could be integrated in the model, though. For instance, the deliberative mindset was associated with more comprehensive information search and longer decision times, as the eye movement and response time analyses in Experiment 2 revealed. This could be represented in the aDDM by a scaling parameter for the threshold separation. The increased separation of boundaries could appropriately represent the idea that more evidence needs to accumulated in favor of one choice option before a decision can be made when decision makers are in a deliberative mindset. By contrast, the implemental mindset resulted in a comparatively greater focus on the probability attributes of risky choices. This influence seems more difficult to integrate in the aDDM, but one could think of a scaling parameter that determines the degree to which probabilities are weighted when decision makers integrate probabilities with outcomes to assess the subjective utility of alternative gambles in the lottery choice task.

Clearly, these proposals require more elaboration and, of course, empirical testing. Several aspects should be considered when designing experiments to test the idea that the deliberative mindset may be associated with greater threshold separation, or that the implemental mindset’s impact on how attention is distributed to particular attributes of alternative choice options affects the process of value integration described by the drift diffusion parameter. First, different decision attributes that jointly determine the value (i.e., utility) of alternative choice options must be clearly dissociable. This is the case in the lottery choice paradigm, when presenting four pieces of information per gamble, as done in Experiments 2 and 3, but it may prove more difficult in other paradigms. Second, both the standard and the attentional drift diffusion model have so far mainly been used to model relatively fast decision processes. For instance, Ratcliff and McKoon (2008) recommended that the model should only be applied to fast binary-choice decisions with mean response times of no more than 1500 ms. Although recent evidence validated the
drift diffusion parameters in choice paradigms that involved slow decisions (i.e., up to approx. 8000 ms, see Lerche & Voss, 2019), it remains unclear whether the relatively complex, and even slower decisions in the lottery choice task (e.g., up to 12500 ms for difficult decisions in Experiment 2) could be appropriately modelled as noisy diffusion processes of evidence accumulation. Future research may take up this line of reasoning as a possibility to incorporate motivational and volitional processes into a formal choice model that is built on attention.

With regard to the deliberative and implemental mindsets, the empirical work in the scope of the present dissertation has shown that two of their main characteristics, i.e., the deliberative mindset’s open-mindedness to all kind of information and the implemental mindset’s cognitive tuning toward feasibility-related information, predicted decision processes under risk, even though lottery choices remained unaffected. Yet, there was at least one other well-established property of the mindsets which could be expected to influence economic decisions. Earlier research demonstrated that the implemental mindset went along with optimistically biased processes of self-enhancement and self-protection. These biased processes manifested, for instance, in terms of a reduction of the perceived vulnerability to risks (Taylor & Gollwitzer, 1995), improved evaluations of the self (Bayer & Gollwitzer, 2005), and increased overconfidence in males (while females overcame their underconfident views on their own skills und judged the latter more realistically when in an implemental mindset; Hügelschäfer & Achtziger, 2014). By contrast, the deliberative mindset, was found to promote realistic assessments of one’s own future performance (e.g., Armor & Taylor, 2003).

The idea that mindset differences in (illusory) optimism could affect economic decisions and their processes was not further considered in the present dissertation. It would, however, certainly be worthwhile to deepen the reflection upon this proposition. Generally speaking, decision makers seem to uphold surprisingly optimistic views about their own future, even when present events do not provide any good reason for high levels of optimism (e.g., Garrett & Sharot, 2014; Sharot, Korn, & Dolan, 2011). More concretely, people tend to underestimate the likelihood of becoming the victim of a violent crime, they typically assume to live longer and healthier than the comparable average, and they heavily overestimate their opportunities in the labor market. This phenomenon of rather unrealistic subjective estimations of future life events’ likelihood
of happening seems to be an expression of a more general bias that affects our thinking and decision making: the optimism bias (see also Jefferson, Bortolotti, & Kuzmanovic, 2017; Sharot, 2011). While optimism in thinking about the future is undoubtedly beneficial in many situations, it may have serious downsides in others (see also Oettingen, Sevincer, & Gollwitzer, 2019).

Linking the well-established finding of overly optimistic thinking about the future to the notion of illusory optimism in goal-directed action, as is characteristic for the implemental mindset, the question arises how these phenomena could be related. In particular, would an implemental mindset boost unrealistic optimism? What is the role of volitional processes in containing the dangers of exaggerated optimism, for instance, in the case of escalating commitment (e.g., Staw, 1981)? Could an intervention targeted at de-biasing unrealistic optimism be based on the deliberative mindset, since it supports realistic assessments of one’s own skills and future performance? Yet more interesting, perhaps, is the question of how financial incentives relate to illusory optimism. Would it be possible, for instance, to reduce unrealistic optimism by encouraging realistic evaluations of future events through incentivization? Initial evidence exists that emphasizes the robustness of the optimism bias, even in the face of realistic feedback and monetary rewards offered for realistic assessments (e.g., Garrett & Sharot, 2017; Thies, 2018). However, more research is required to further explore the motivational and volitional processes that shape people’s fundamentally unshakeable optimistic attitudes about their own future in general, and in relation to economic decisions in particular.

On a side note related to the question of de-biasing unrealistic optimism, the present dissertation delivered some interesting implications for the development of interventions aimed at promoting desirable behavior. Such interventions may be grounded on financial incentives, the deliberative and implemental mindsets, or both. Interestingly, the findings from Experiment 1b implied that incentive-based interventions could be designed in a more cost-effective way, since the absolute amount of the monetary reward did not appear to affect decisions. In contrast, it seemed more effective to emphasize the direct link between the incentive and performance, i.e., the incentive salience. Hence, it could be argued that so long as incentives are highly salient, in the sense that their contingency on performance is clearly stated, increasing the absolute
amount may provide no further benefit beyond what can be achieved by offering relatively low monetary rewards.

It should be noted, though, that based on the results of Experiment 1b, the possibility cannot be ruled out that increasing the absolute amount of incentives produced counteracting effects on decision processes. As mentioned above, recent research found that higher incentives may both, increase the reliance on fast but potentially faulty decision heuristics and the effort invested in the task at hand (Achtziger & Alós-Ferrer, 2014; Achtziger et al., 2015; Alós-Ferrer et al., 2019). In consequence, these effects could have canceled each other out on average, suggestive of the false impression that higher incentives did not impact decisions. Experiments 1a and 1b used only decision times to trace the cognitive effort decision makers invested in the task. Further measures that could indicate effort independently from decision time would be required to rule out the possibility of such antagonistic effects of financial incentives. To track cognitive effort independently from decision times, one could use, for instance, pupil dilation measurement (Alós-Ferrer et al., 2019; Kahneman & Beatty, 1966) or functional near infrared spectroscopy (fNIRS; Causse, Chua, Peysakhovich, Campo, & Matton, 2017; Vassena, Gerrits, Demanet, Verguts, & Siugzdaite, 2019). This limitation of Experiments 1a and 1b, namely that cognitive effort could not be disentangled from other contributors to decision time, should be overcome in future research through the use of process tracing methods that facilitate a more precise measurement of cognitive effort.

As noted above, the deliberative and implemental mindsets have strong potential to serve as relatively unobtrusive, readily available interventions to promote desired behavior in a variety of settings. Dependent on the task set, the deliberative mindset could support performance in tasks in which open-mindedness to incoming information, the thorough and impartial weighing of evidence, and comprehensive information search improves performance. By contrast, the implemental mindset may improve performance in tasks that are supported by fast decisions, increased persistence, or reliance on decision heuristics. Interestingly, the deliberative and implemental mindsets may, under certain circumstances, have surprisingly greater effects on economic performance than financial incentives (compare, for instance, incentive effects and mindset effects in the Bayesian updating paradigm; Achtziger & Alós-Ferrer, 2014; Li et al., 2019). The present work
added to this evidence, providing robust evidence for deliberative and implemental mindset effects on decision processes under risk.

Finally, it should not go unnoticed that the experiments in the scope of the present dissertation replicated a number of well-established findings from the decision research literature. Though, in some cases, the evidence presented here added some interesting insights to the established phenomena and qualified the previous observations. In Experiments 1a and 1b, age predicted decision times, emphasizing that decision making may change over the lifespan (Mata et al., 2011; Tymula, Rosenberg Belmaker, Ruderman, Glimcher, & Levy, 2013). Interestingly, age also predicted choices in the CRT (but not in the probability judgment task), i.e., older participants were more likely to respond correctly the CRT problems, even when controlling for individual differences in numeracy. In line with earlier findings (Frederick, 2005), males were found to outperform females in the CRT (but again, not in the probability judgment task). Yet, this performance difference was not entirely attributable to individual differences in subjective numeracy, as suggested in previous research (Zhang et al., 2016).

Experiment 2 replicated the task difficulty effect on decision times, confirming that decision times in the lottery choice paradigm validly reflected cognitive effort (e.g., Rahn et al., 2016b). Yet, the difficulty-effort relation also appeared to rely on incentivization, as the different rank order under different incentive schemes revealed. As discussed earlier, Experiment 2 replicated the common finding that the final fixation predicted the choice (e.g., Glaholt & Reingold, 2009; Krajbich et al., 2010; Orquin & Mueller Loose, 2013; Stewart et al., 2016). An interesting addition to this finding was that choices were better predicted by the last fixation for decision makers in a deliberative mindset than implemental decision makers. This finding underlined the potential benefits of incorporating systematic influences of motivation and volition on decision processes into formal choice models. Also replicating earlier work (Fiedler & Glöckner, 2012), Experiments 2 and 3 confirmed that the mean expected value of lotteries determined the pupillary response in the risky choice paradigm. Yet, the analyses also indicated that the maximum outcome of the lottery, which presumably drives differences in mean expected values, was the more potent predictor of pupil size change over time.
Replicating earlier findings (E. Brandstätter & Körner, 2014; Franco-Watkins & Johnson, 2011; Göckner & Herbold, 2011), Experiments 2 and 3 showed that zero-outcomes were special gamble attributes that were disregarded in terms of visual attention. While there was robust evidence for the idea that this was the case because zero-outcomes were more easily processed since they did not require integration with probabilities, Experiment 3 added an important aspect to this phenomenon. That is, novel evidence was provided for the idea that, in addition to being more easily processed, zero-outcomes were also interpreted as losses (when all other outcomes were gains) and elicited strong affective arousal, as well as a pronounced motivational tendency of avoidance. In combination, these zero effects on attention, affect, and motivation resulted in a considerable choice bias.

Indeed, the zero effect in risky choices seemed to outweigh the certainty effect (i.e., the decision makers’ preference for sure gains) when these two decision biases were pitted against each other. While the certainty effect was replicated (e.g., Kahneman & Tversky, 1979), Experiment 3 raised some doubts regarding its relative strength in decisions under risk. Despite the successful replication of the certainty effect, the evidence for its impact on behavioral choices was rather weak. Specifically, the certainty effect appeared to be minimized when it was not combined with a zero effect to support it by driving choices away from the zero gain option. It is not least because of this finding that one final take-away message from the present dissertation ought to be about the significance of replication in research on judgment and decision making. Replication studies are important, not only because they enhance the confidence in the findings of earlier research, but also because they bear the potential to add important qualifications to the basic assumptions that much of the empirical and theoretical work in decision research is built upon.
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Appendix A: Experiments 1a, 1b

Appendix A1: Decision problems used in Experiments 1a and 1b.

CRT problems

Pizza
Five pizza chefs can make five pizzas in five minutes. How long would it take 100 pizza chefs to make 100 pizzas?
(adapted from Frederick, 2005)

Ivy
To decorate the front of his new home, Peter planted green ivy that will climb up the facade. The ivy is fast-growing and will double the area it covers every day. If it takes 28 days for the ivy to cover the entire front of Peter’s home, how long would it take for the ivy to cover half of the facade?
(adapted from Frederick, 2005)

Water
A dog drinks one barrel of water in 6 days, and a cat drinks one barrel of water in 12 days. How long would it take the dog and the cat to drink one barrel of water together?
(adapted from Toplak, West, & Stanovich, 2013)

School
Bertha received the 10th highest and the 10th lowest grade on a history test given in an undergraduate class. How many students are in Bertha’s class?
(adapted from Toplak, West, & Stanovich, 2013)

Watch
Susan buys an antique watch on a flea market for $40. She sells it for $50, buys it back for $60 and finally sells it for $70. How much profit has she made?
(adapted from Toplak, West, & Stanovich, 2013)

Base-rate neglect problems

Undergrads
One hundred undergraduate students applied for a part-time job. Of the applicants, 15 were humanities students, and 85 were science students. Mike was one of the 100 students who applied for the job. His name was randomly chosen by the computer to participate in the first day of interviews. Mike is 23 years old, he likes to travel, and he was quite a good student in high school. His preferred subjects were English poetry, modern art, and sports.
Which of the following is more likely?
(A) Mike is one of the humanities students.
(B) Mike is one of the science students.
(adapted from Ferreira, Garcia-Marques, Sherman, & Sherman, 2006)

Army
One hundred men from the U.S. Army Special Forces were selected for a dangerous secret mission in South America. Ten of these men are officers, and 90 are privates. Bob is a veteran from the Vietnam War. He is often called for special missions, and he is used to commanding men under extremely difficult situations. Last year he was promoted and was decorated by the U.S. president for his accomplishments in the army and for his exceptional qualities of leadership.
Which of the following is more likely?
(A) Bob is one of the officers.
(B) Bob is one of the privates.
(adapted from Ferreira et al., 2006)
Engineer
Several psychologists interviewed a group of people. The group included 22 engineers and 78 lawyers. The psychologists prepared a brief summary of their impression of each interviewee. The following description was drawn randomly from the set of descriptions: Jack is 45. He is conservative, careful, and ambitious. He shows only little interest in political issues and spends his free time mostly on his hobbies, which include carpentry, biking, and solving complicated Sudoku puzzles.

Which of the following is more likely?
(A) Jack is an engineer.
(B) Jack is a lawyer.
(adapted from Tversky & Kahneman, 1974)

Africa
In an African country, there are 5 million citizens. Wealth is divided very unequally between them because 30% of the family incomes are below the poverty line. John has to travel long distances for his work to provide for his family. His wife takes care of the eight children, the older ones among them have own jobs.

Which of the following is more likely?
(A) John’s family income is above the poverty line.
(B) John’s family income is below the poverty line.
(adapted from Ludwig, Ahrens, & Achtziger, 2019)

Piercing
A study tested 1000 people. There were seven sixteen-year old teenagers and 993 fifty-year olds. Linda is one of the participants, she was chosen randomly. Linda likes to wear tight shirts and jeans. She enjoys listening to rap music and loves dancing. Linda has a small nose piercing.

Which of the following is more likely?
(A) Linda is sixteen years old.
(B) Linda is fifty years old.
(adapted from De Neys & Glumicic, 2008)

Conjunct probability problems

Physician
A local hospital's chief physician wants one of the assistant doctors to compose a lecture course. Doctor A is very busy but also experienced in the field. Due to a lack of time she can meet only 70% of the quality standard. Alternatively, the chief physician could divide the task between two less experienced assistants who would be able to invest more time. Doctor B can meet 75% of the quality standard, Doctor C can deliver 80% of the standard.

Who should the chief physician choose for the job?
(A) Doctor A.
(B) Doctor B and Doctor C.
(adapted from Ludwig, Ahrens, & Achtziger, 2019)

Soccer
A soccer team coach reflects on the line-up for the upcoming weekend. It is an important game and the line-up is tricky because both of the team's top strikers are still recovering from injuries. Due to their injuries, they have a reduced level of fitness and can only deliver 60% and 70% of their usual performance, respectively. Instead of the injured strikers, the coach could strengthen the defense and send a single attacking midfielder to the forward line. Since this player would not be in his preferred position, he could only deliver 50% of his usual performance.

Who should the coach send to the forward line?
(A) The two strikers.
(B) The midfielder.
(adapted from Ludwig, Ahrens, & Achtziger, 2019)

Gamble
Emma and Sophia had dinner together at a fancy restaurant. After finishing their
meals, Emma suggests a game to decide who would have to pay the check. Sophia may choose between two games: She either flips two coins and if both show "heads", Sophia will have to pay the check. Both coins have a 50/50 chance to show "heads". Alternatively, Sophia can roll a dice. If the dice shows either a one or a six, then Sophia will have to pay the check. Thus, Sophia's chances of "winning" are 33% in the dice game.

Which of the options should Sophia choose so she will not have to pay the check?

(A) Flip two coins.
(B) Roll a dice.

(adapted from Ludwig, Ahrens, & Achtziger, 2019)

Project
An external project manager consults a company on a complex, long-term project. She offers two options for the project. Option A is to divide the project into four smaller sub-projects. The consultant thinks that this facilitates the implementation and that each sub-project will be able to meet the deadline with a probability of 85%. Each sub-project must be finished to complete the overall project. For Option B, the integrated implementation process of the project without division into sub-projects, she estimates a likelihood of meeting the deadline of 60%.

Which option should the company choose?

(A) Option A.
(B) Option B.

(adapted from Ludwig, Ahrens, & Achtziger, 2019)

Beauty
A company that makes beauty products is about to launch a new product line. The marketing department wanted to begin with the promotion of this new line as quickly as possible. To do this they can either deliver all the promotional work to a large publicity agency, or they can divide the promotional work between two smaller publicity agencies. The large agency has a record of meeting deadlines of 60%. One of the smaller agencies has a record of meeting deadlines of 80%, and the other has a record of meeting deadlines of 70%. The marketing department can begin the promotion only when all the promotional work is ready to be used.

Which option should the company choose?

(A) The large agency.
(B) The two smaller agencies.

(adapted from Ferreira et al., 2006)
Table B1. Lotteries per category of the decision task used in Experiment 2. Each lottery consisted of two gambles (Gamble A, Gamble B).

<table>
<thead>
<tr>
<th>Category of the decision task</th>
<th>Gamble A</th>
<th>Gamble B</th>
</tr>
</thead>
<tbody>
<tr>
<td>CERT</td>
<td>40, .40; 100, .60</td>
<td>0, .20; 100, .80</td>
</tr>
<tr>
<td>PRO</td>
<td>0, .30; 90, .70</td>
<td>0, .20; 100, .80</td>
</tr>
<tr>
<td>MED</td>
<td>45, .60; 65, .40</td>
<td>0, .33; 80, .67</td>
</tr>
<tr>
<td>MED (Add. Cert)</td>
<td>0, .33; 80, .67</td>
<td>0, .33; 80, .67</td>
</tr>
<tr>
<td>SIM</td>
<td>5, .60; 47, .40</td>
<td>5, .60; 47, .40</td>
</tr>
<tr>
<td>CERT (Pro)</td>
<td>0, .20; 100, .80</td>
<td>0, .20; 100, .80</td>
</tr>
<tr>
<td>7/198</td>
<td>1/1002/2002/67/69/48/24/1/7/198</td>
<td></td>
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</table>

Table B1. Lotteries per category of the decision task used in Experiment 2. Each lottery consisted of two gambles (Gamble A, Gamble B).
### Appendix C: Experiment 3

<table>
<thead>
<tr>
<th>Category of the decision task</th>
<th>Gamble A</th>
<th>Gamble B</th>
<th>Gamble A</th>
<th>Gamble B</th>
<th>Gamble A</th>
<th>Gamble B</th>
<th>Gamble A</th>
<th>Gamble B</th>
</tr>
</thead>
<tbody>
<tr>
<td>CERT</td>
<td>0.50</td>
<td>0.45</td>
<td>0.50</td>
<td>0.45</td>
<td>0.50</td>
<td>0.45</td>
<td>0.50</td>
<td>0.45</td>
</tr>
<tr>
<td>CERT 99</td>
<td>0.40</td>
<td>0.30</td>
<td>0.30</td>
<td>0.40</td>
<td>0.30</td>
<td>0.40</td>
<td>0.30</td>
<td>0.40</td>
</tr>
<tr>
<td>CERT 100</td>
<td>0.55</td>
<td>0.45</td>
<td>0.55</td>
<td>0.45</td>
<td>0.55</td>
<td>0.45</td>
<td>0.55</td>
<td>0.45</td>
</tr>
<tr>
<td>SIM</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Each gamble consisted of two outcomes (X, Y) and two probabilities (p, q). Each lottery consisted of two gambles (Gamble A, Gamble B).

Table C1: Lotteries per category of the decision task used in Experiment 3. Each lottery consisted of two gambles (Gamble A, Gamble B).
Table C2. Results of the linear mixed-effect model analyses on the fraction of fixations directed at the four outcomes of one lottery (in percent), separately for four lottery types. Outcome (A1, A2, B1, B2) was entered as a fixed effect, lotteries and participants were entered as random effects. The table shows fixed effect estimates and .95 confidence intervals for all outcomes. In all ZERO and CERTZERO lotteries, Outcome A2 was a zero-outcome.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>CERT100</th>
<th>CERT99</th>
<th>ZERO</th>
<th>CERTZERO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (Outcome A1)</td>
<td>23.98</td>
<td>22.90, 25.07</td>
<td>28.05</td>
<td>27.03, 29.07</td>
</tr>
<tr>
<td>Outcome A2</td>
<td>0.24</td>
<td>-1.29, 1.77</td>
<td>-5.84</td>
<td>-7.29, -4.40</td>
</tr>
<tr>
<td>Outcome B1</td>
<td>0.61</td>
<td>-0.92, 2.14</td>
<td>-2.85</td>
<td>-4.30, -1.41</td>
</tr>
<tr>
<td>Outcome B2</td>
<td>3.22</td>
<td>1.69, 4.75</td>
<td>-3.51</td>
<td>-4.95, -2.06</td>
</tr>
</tbody>
</table>

Note. SIM lotteries not included. The fixed effect of outcome did not affect the distribution of fixations on the four outcomes in that lottery type.