Robo-Advisory and Decision Inertia
Experimental Studies of Human Behaviour in Economic Decision-Making

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> “Two important facts about our minds: we can be blind to the obvious, and we are also blind to our blindness.”

Daniel Kahneman "Thinking, fast and slow" (2011)

Contents

Abstract

Investing in the stock market is a complicated and risky undertaking for private households. In particular, private investors face numerous decisions: for instance, whether to invest in stocks or bonds, buy passively or actively managed investment products, or try something new like Bitcoin. They must decide where they can get independent financial advice, and whether this advice is trustworthy.

As a consequence, information systems researchers design and build financial decision support systems. Robo-advisors are such decision support systems aiming to provide independent advice, and support private households in investment decisions and wealth management. This thesis evaluates robo-advisors, their design and use and thus their ability to support financial decision-making. Addressing this research need, my thesis is organized in three parts (*part I-III*) consisting of four quantitative experimental studies, two qualitative friendly-user-studies, and one qualitative interview study.

In *Part I*, Chapter 3 examines how robo-advisors can be designed for inexperienced investors. In particular, I derive design recommendations for the development of robo-advisor solutions and evaluate them in a three-cycle design sciences process. Requirements related to the clusters *ease of interaction*, *work efficiency*, *information processing* and *cognitive load* are identified as key elements for robo-advisory design.

In *Part II*, Chapter 4 focuses on an important bias in economic decision-making - decision inertia, the tendency to repeat a decision regardless of the consequences. As a result, a decision-maker can make repeated suboptimal investments. To understand this bias more deeply, I investigate decision inertia in a general experimental setting and identify motivational and cognitive drivers of this phenomenon. Thus, I relied on behavioural, on self-reported, and on bio-physiological measures in three laboratory studies.

In *Part III*, Chapter 5 specifies the findings from Part II to find and evaluate strategies to reduce decision inertia in financial decision support systems. For that purpose, I investigate two nudges (design features) to reduce inertia in investment decisions. My results suggest that defaults and warning messages can help participants to overcome decision inertia. Furthermore, the results illustrate that designers have to be careful not to push decision-makers into the decision inertia bias by accident.

In summary, this thesis gives design recommendations for practitioners and scholars building robo-advisors. The insights can help to develop robo-advisors, and to increase advisor quality by considering decision inertia in the system design phase and consequently, it illustrates how to counteract this malicious decision bias for private investors.

List of Publications

Selected parts of this work are published or working papers. Thus, this thesis is based on the following publications:

- Jung D, Dorner V, Glaser F, Morana S (2018): Robo-Advisory - Digitalization and Automation of Financial Advisory, Business and Information Systems Engineering (BISE) [section 3.1].
- Jung D, Dorner V, Weinhardt C, Pusmaz H (2018): Designing a Robo-Advisor for Risk-Averse, Low-Budget Investors, Electronic Markets (EM) [section 3.2 - 3.8].
- Jung D, Dorner V (2017): Decision Inertia and Arousal - Using NeuroIS to Analyze Bio-Physiological Correlates of Decision Inertia in a Dual-Choice Paradigm. In Proceedings of the Retreat on NeuroIS 2017, Gmunden. Springer International Publishing [section 4.2.2, and 4.2.1].
- Jung D, Dorner V, Erdfelder E, Bröder A (in press): Differentiating Motivational and Cognitive Explanations for Decision Inertia, accepted at Journal of Experimental Psychology [section 4.3, 4.4, and 4.6].
- Jung D, Stäbler J, Weinhardt C (2018): Investigating Cognitive Foundations of Decision Inertia. HeiKaMaxY Discussion Paper. KIT Scientific Publishing [section 4.3, and 4.5].
- Jung D, Weinhardt C (2018): Robo-Advisors and Financial Decision Inertia: How Choice Architecture Helps to Reduce Inertia in Financial Planning Tools. In Proceedings of the International Conference of Information Systems (ICIS) [section 5].
- Jung D, Erdfelder E, Glaser F (2018): Nudged to win - Designing robo-advisory to overcome decision inertia. In: Proceedings of the 26th European Conference on Information Systems (ECIS 2018) [section 5].

Other related Publications

- Glaser F, Iliewa Z, Jung D, Weber M (2018): Towards Designing Robo-Advisors for Inexperienced Investors with Experience Sampling of Time-Series Data, In: Proceedings of the Retreat on NeuroIS 2018, Vienna. Springer International Publishing.
- Jung D, Glaser F, Köpplin W (2018): Robo-Advisory - Opportunities and Risks for the Future of Financial Advisory. In: Nissen V - Advances in Consulting Research - Recent Findings and Practical Cases. Springer International Publishing.

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1 Introduction

1.1 Relevance and Research Gap

Many people avoid making financial decisions, for example how to save money for retirement, a house or the education of their children and they consider these kinds of decisions to be difficult and complex (Fisch, Laboure, Turner, & Center, 2017; Looney & Hardin, 2009; Wood, 1986). Moreover, even people motivated to make financial decisions encounter overwhelming complexity and variety among the available financial products and investment possibilities (Minch & Sanders, 1986). Previous research illustrates that private investors have coped with this complexity only to a limited extent, due to their scarce cognitive resources (e.g., processing speed, knowledge, or willpower), and consequently make mostly simplified or intuitive economic decisions (see e.g. Benartzi and Thaler (2007); Bazerman, Loewenstein, and Moore (2002); Barber and Odean (2001)).

In order to overcome these shortcomings of human decision-making, information systems researchers aim to design and develop financial decision support systems. These information systems help users to handle the complexity of financial decision-making and make rational or deliberative decisions (Fisch, Laboure, et al., 2017). A novel approach in doing so is robo-advisory (Phoon & Koh, 2017; Sironi, 2016). Building on various assistance components, robo-advisors guide users through a self-assessment process. By making usage of the assessed user profile, the robo-advisor computes different investment recommendations and supports individual portfolio selection. Furthermore, the robo-advisor allows one to maintain and rebalance a portfolio after the investment. Since robo-advisors act as merely an economic platform between providers of financial products and users (see Figure 1), studies suggest that conflicts of interest (e.g., principal agent dilemma) are also less common than in traditional asset management at a bank (Phoon & Koh, 2017; Sironi, 2016).

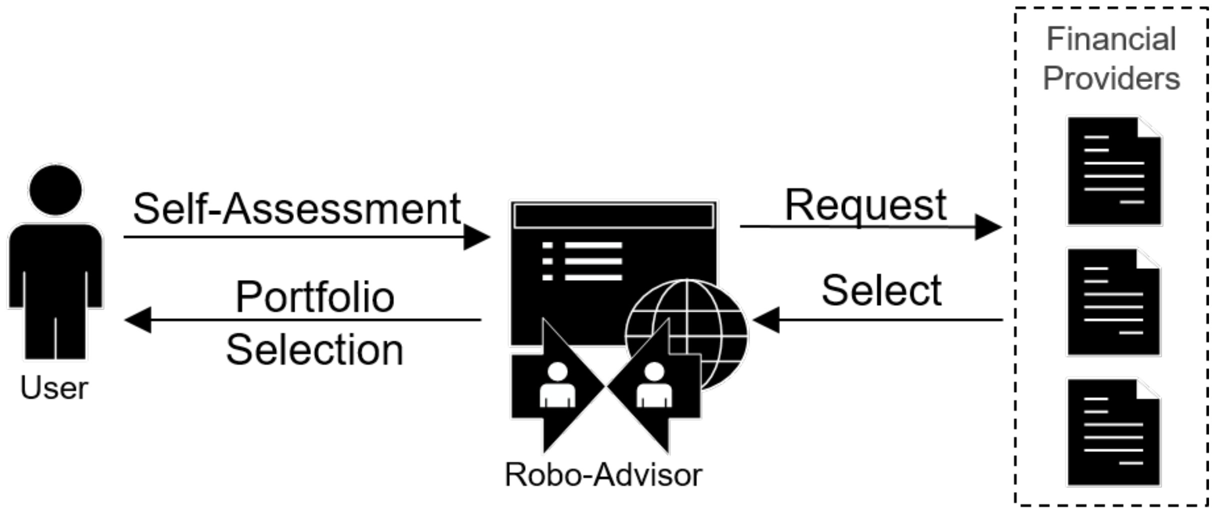

Figure 1: Robo-advisors act as an economic platform between private households (users) and financial product providers.

Many robo-advisors disclose their business models and pass their brokerage directly to their users (see e.g., Visual Vest or Betterment). Furthermore, robo-advisors provide financial training, financial encyclopaedias, or further information about the investment process to support their users in expanding their financial knowledge. If the user's investment decision is made, robo-advisors offer an easy way for private households to maintain and manage investment portfolios, building on mobile apps or web applications.

Even though robo-advisors represent a promising solution for many potential users, the questions remain whether robo-advisors can really replace traditional human advisory and asset managers, and of what the limits of robo-advisor services are. In particular, the design of user-interaction and self-assessment processes, along with the quality of the advisory service, are still controversial. For instance, this year, the well-known German consumer protection organisation Öko-Test issued a study of robo-advisors regarding their advisory service (Sternberger-Frey, 2018). The organisation investigated the most popular 24 robo-advisors on the German private customer market. None of the advisors tested were free of any crucial defects: "All portals have some mismatch [...] either they lack transparency or they do not really satisfy their claim to be a robo-advisor" (own translation) (Sternberger-Frey, 2018, p.110). These results are corroborated by further recent evidence, illustrating that the configuration process of many robo-advisors is poorly designed and does not meet the requirements of unexperienced users (Tertilt & Scholz, 2017; Sternberger-Frey, 2018). On the other hand, successful user-interaction and assessment is crucial for building a user profile, and a portfolio recommendation. It is necessary to provide an adequate advisory based on the user preferences, risk-attitude and financial circumstances (Phoon & Koh, 2017). However, in a recent study Tertilt and Scholz report that they "hardly see any advantages from robo-advisory in the assessment of risk tolerance and risk capacity; or in the quality of the recommended portfolios" (Tertilt & Scholz, 2017, p. 19). Hence, it is not surprising that in information system research the advisory service quality of these robo-advisor systems is criticised (Tertilt & Scholz, 2017), while some even go so far to question the general usefulness of robo-advisors per se (Fein, 2015). Taking all this together, robo-advisory scholars and practitioners face two research challenges:

The first challenge is that robo-advisory has hardly been researched so far, and there is a lack of literature with methodological knowledge on how such systems can be built and designed. The reason is that robo-advisory remain a very novel tool, so best-practices have not yet been developed. This absence becomes all the more clear considering that most robo-advisors have not even been on the market for three years. The oldest robo-advisor, Betterment, was founded in 2010 (Phoon & Koh, 2017). Furthermore, one of the largest scientific search engines, Google Scholar, delivers just 204 possible hits for the term *robo-advisory* in March 2018.

Additionally, previous research in the field of information systems identifies that digitalization of social and interactive processes - such as financial consulting - conflicts with fundamental human expectations about interaction and communication in advisory scenarios (Rogers, Sharp, & Preece, 2011; Bannon, 1995). Robo-advisors replace existing human-based services with digital ones and thus face these types of problems. So far, information systems research has not yet sufficiently determined how human-based services can be transformed into digital robo-based services. This transformation raises many questions concerning the expectations of the users or the general design of the assessment and advisory process, among other things. Initial studies illustrate that transparency, trust-building and the balancing of information asymmetries play a crucial role in the design and development of partially digitalized financial advisory (Ruf, Back, & Burkhardt, 2016; Heinrich, Kilic, Aschoff, & Schwabe, 2014; Nussbaumer, Matter, & Schwabe, 2012; Nussbaumer, Matter, à Porta, & Schwabe, 2012). However, it remains unclear how these issues can be considered in system design, and which design principles and decisions result from these requirements. Recent studies suggest that a sophisticated user interface is a key issue for scholars and practitioner designing and developing robo-advisors (Sternberger-Frey, 2018; Ludden, Thompson, & Mohsin, 2015). This suggestion underlines the need for general guidelines for robo-advisory design.

A second challenge confronting robo-advisor designers is that the "chances of robo-advisory actually becoming a true disruptive force, depends on the quality of their advice" (Tertilt & Scholz, 2017, p.3). However, both financial advisory and its design are difficult (Fisch, Turner, & Center, 2017; Fisch, Laboure, et al., 2017). It is well known from behavioural finance and decision-making research that if people are overwhelmed with complexity they make an effort-accuracy trade-off (Johnson & Payne, 1985). That is people try to find a balance between effortful deliberative thinking and the potential result of their decision-making. People are therefore face a tension between deliberative, effortful processes and intuitive, effortless processes (Alós-Ferrer & Strack, 2014; Kahneman, 2003). In consequence, for complicated decisions, so-called heuristics or "rules of thumb"are applied, based on intuitive processes (Gigerenzer, 2008), which reduces the effort required to make the decision yet delivers satisfactory results in most real-world scenarios (Gigerenzer & Brighton, 2009). This kind of interaction of so-called deliberative (or System 2 processes), and intuitive (or System 1 processes) systematically shapes economic decision-making, as will be discussed in Section 2.1.

However, these different types of judgement and decision-making are generally used as theoretical explanations for various decision anomalies in various studies in behavioural economics and finance (Alós-Ferrer & Strack, 2014; Dhar & Gorlin, 2013; Barberis & Thaler, 2003). Although the decision support literature reports many decision biases that result from heuristic-intuitive decision-making (see Arnott (2006) for an overview of biases in decision support systems), my work focuses on a particular bias that plays a relevant role in financial decision-making: decision inertia, or the tendency to repeat a decision regardless of the consequences (Alós-Ferrer et al., 2016; Dutt & Gonzalez, 2012).

Numerous experiments have demonstrated that decision inertia is a relevant issue in economic decision-making (see e.g., Alós-Ferrer et al. (2016); Erev and Haruvy (2013); Charness and Levin (2005); Madrian and Shea (2001)), and that it has serious implications for decision support system design. Decision inertia pushes users towards repeating previous (suboptimal) decisions, such that unsuccessful strategies are repeated, and that people stick to their default decisions even if they are not economically advantageous. From a decision support perspective, understanding the drivers of decision inertia is crucial for decision-support system design. By understanding the reasons decision inertia occurs, decision support systems aim to provide the basis for detecting and counteracting decision inertia by way of system design.

Furthermore, it remains unclear the extent to which the interface of financial decision support systems like robo-advisors reduces or even reinforces known biases and errors.

The two challenges in the context of the choice architecture of a robo-advisor can be discussed in a general decision support context, yielding the theoretical framework illustrated in Figure 2. This framework, assumes that a user of a robo-advisor system has individual financial preferences and a specific situation. Building on that situation (and the interaction with the decision support system) the user makes an investment decision. Behavioural research (e.g., Generalized Dual-Processing Theory) postulates that the investment decision is made through an interaction of intuitive and deliberative processes. The robo-advisor measures the behaviour of the user and supports the decision-making by interventions or feedback (response). This more general theoretical framework for financial decision-making in a decision support system guides the experimental analysis in Parts I-III.

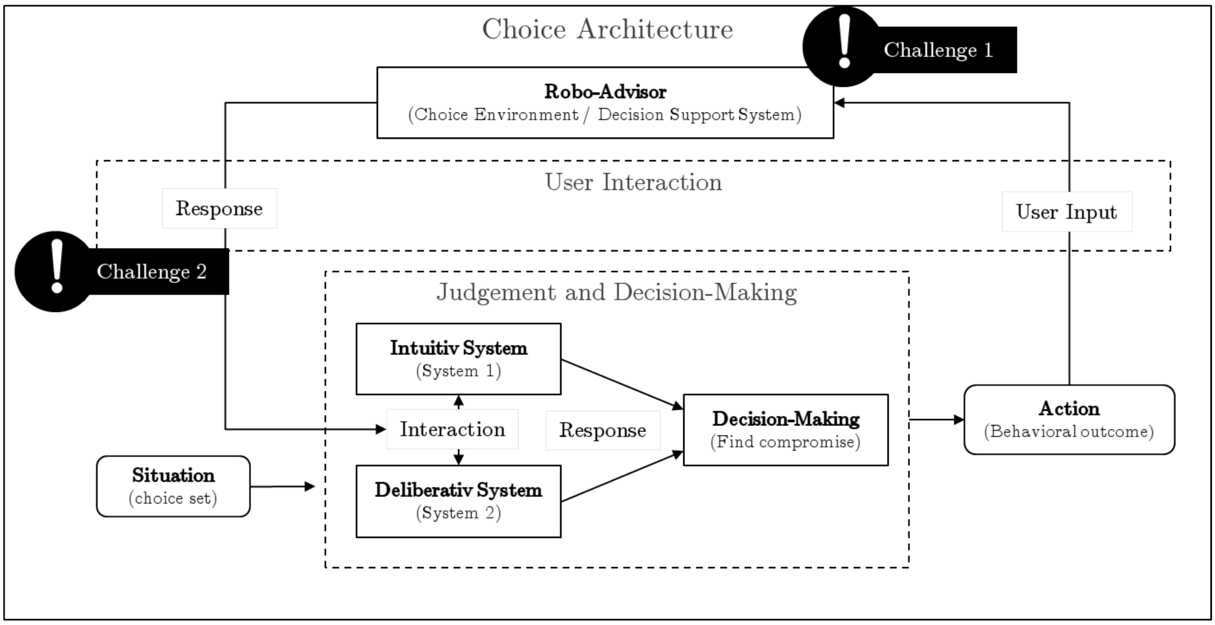

Figure 2: Conceptual model of the choice architecture and usage of a robo-advisory in financial decision-making, based on Loock et al. (2013), and Thaler (2008)

1.2 Research Questions

As discussed above, robo-advisor researchers facing design problems booth at a general level and at a bias-specific level. However, knowledge is limited as regards designing robo-advisory, and the foundations and cognitive drivers of bias-sensitive design (in particular decision-inertia sensitive). Should the knowledge gap persist, the digitalization of financial advisory may be difficult to achieve. A need therefore arises to investigate and build theory about robo-advisory, manifesting in the following research questions:

- **Research question 1 (RQ1): How can a robo-advisor be designed for unexperienced investors?**
  In this first step, I focus on the general design of robo-advisory. Information systems research lacks methodological knowledge and design guidelines concerning robo-advisors. For that purpose I conducted a three-cycle design science study to derive, test and evaluate design requirements for robo-advisors. These design recommendations provide a preliminary guideline for practitioners and scholars designing robo-advisory solutions.
- **Research question 2 (RQ2): What are the cognitive and motivational foundations and drivers of decision inertia? How can they be distinguished?**
  After establishing a better understanding of decision inertia, I review recent judgement and decision-making research to provide an overarching concept concerning decision inertia. Based on this review I show that existing decision inertia experiments can be generalized into a so called dual-choice belief-updating task Dual-Choice Belief-Updating Task (2CBU), and provide an experimental framework for further investigations. In a second step, I investigate motivational and cognitive processes influencing inertial behaviour in decision-making based on that framework. I underpin these findings by controlling for possible emotional and bio-physiological drivers, and by the disentangling motivational and cognitive foundations of inertia in decision-making.
- **Research question 3 (RQ3): How should the choice architecture of robo-advisors be designed to help users to overcome decision inertia in financial decision-making?**
  Finally, I use findings from the previous study to derive design features (so called digital nudges) to reduce decision inertia in financial decision-making. I systematically design the choice environment of a robo-advisor to guide the user, based on digital nudges towards optimal decision-making (choice architecture approach, (Thaler, Sunstein, & Balz, 2014)). The findings provide a general foundation for decision support system design to overcome decision inertia. Furthermore, these findings sharpen knowledge about decision inertia and are used as a basis to derive methods to counteract decision inertia and illustrate the influence of decision inertia in a real-world scenario.

Following these research questions (as illustrated in Figure 3), I derive and evaluate general design recommendations for robo-advisory (*RQ1*). These findings can be used as general design guidelines for practitioners and scholars.

Following *RQ2*, I try to provide a meaningful conceptual model of decision inertia in decision-making. This model is enriched by two experimental studies conducted to gain a deeper understanding of the cognitive foundations of decision inertia. These findings are generalized

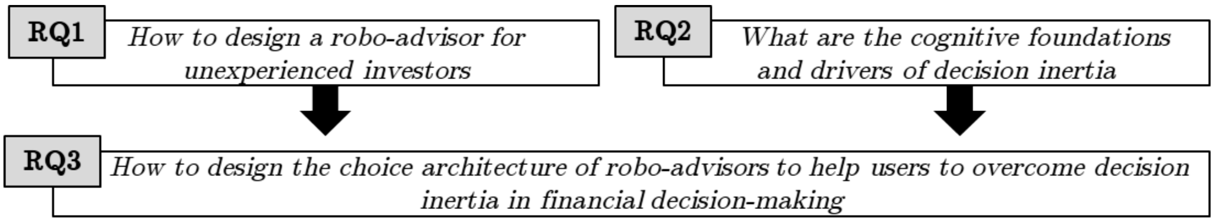

Figure 3: The three research questions targeting the human behaviour in financial decision support systems follow a decision support paradigm.

into methods to counteract decision inertia in a digital choice environment, following a choice architecture approach (*RQ3*). I show that decision inertia plays a relevant role in information systems, and in decision support systems, but can be reduced in strategically designed choice environments.

1.3 Research Design

The research design and the empirical component of the first major unit of this work (*Part I*) originated in industry cooperation with a *large German investment company*, while the second major unit (comprised of both *Part II* and *Part III*) originated in an interdisciplinary research project with the chair of *Cognitive Psychology and Individual Differences*, and the chair of *Experimental Psychology* at the University of Mannheim. The purpose of these projects was, firstly, to better understand human behaviour in robo-advisory, secondly to understand the cognitive foundations and drivers of phenomenon decision inertia, and finally to make these findings usable for information system research. Thus, this work is based on contributions and insights from decision theory, economics, information systems, psychology and neurology.

Building on these interdisciplinary research streams, this research applies generalized dual-processing theory as an overarching theory for human behaviour and decision-making. Human behaviour and decision-making is explained by considering deliberative and intuitive processes (Alós-Ferrer & Strack, 2014; Kahneman, 2003). Both processes form our intention, and consequently result in human behaviour. Generalized dual-processing theory explains judgement and decision-making across all disciplines investigating human behaviour (Alós-Ferrer & Strack, 2014). Applying generalized dual-processing theory, different approaches and frameworks have been proposed to structure behavioural research (see e.g. Mirsch, Lehrer, and Jung (2017); Weinmann, Schneider, and vom Brocke (2016); Thaler and Cass (2008)). Referring to these interdisciplinary guidelines, this research project uses a behavioural-driven research cycle. The behavioural research cycle, provides a framework for understanding, investigating biased decision-making and for deriving counter-methods to overcome it.

With reference to the behavioural research cycle (see Figure 4), the remainder of this work is organized in the following manner: In Chapter 2, I review the theoretical foundations of this work (Generalized Dual-Processing Theory, and Choice Architecture). In the subsequent section, I focus on *RQ1*, following a design science approach setting forth a robo-advisory so-

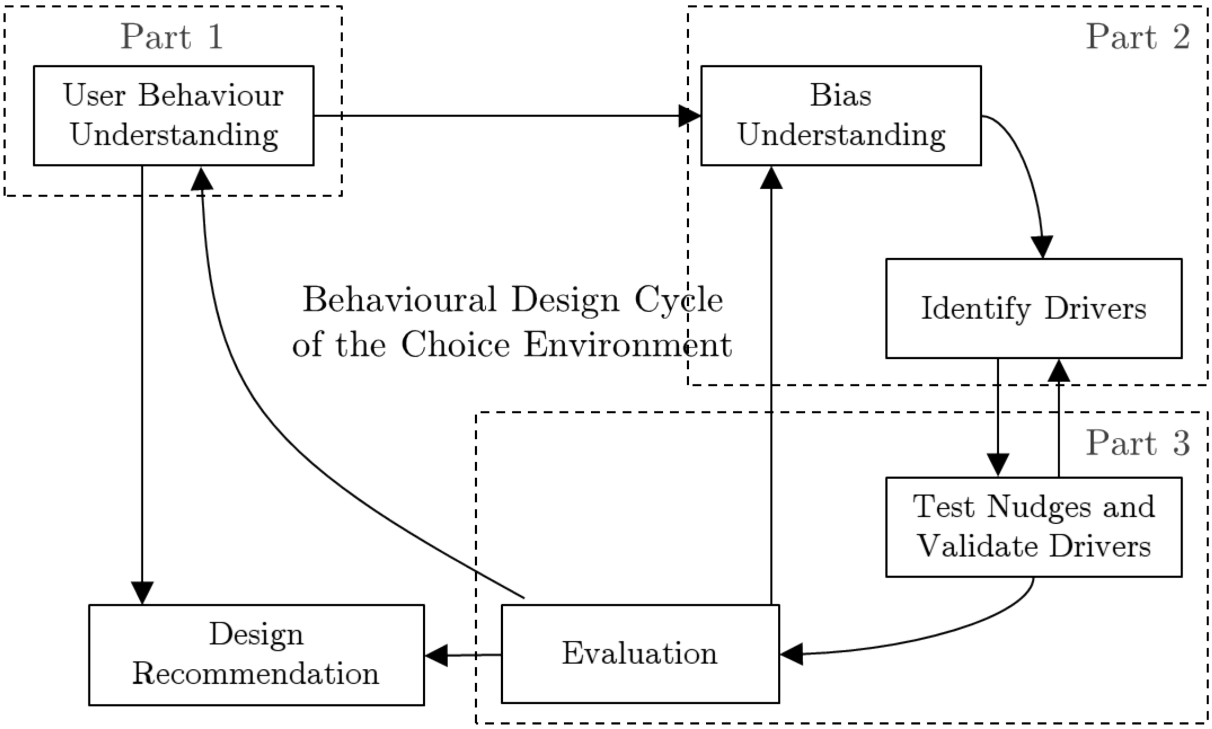

Figure 4: *Research Design* builds on a behavioural design procedure based on the guidelines of Mirsch, T. Lehrer, C. and Jung, R. (2017), Weinmann, M. and Schneider, C. and Vom Brocke, J. (2016), and Thaler, R. Sunstein, C. (2008).

lution for unexperienced investors. The design sciences approach is based on three research cycles shaping and evaluating the derived design recommendations. In the next section, I focus on the cognitive drivers of inertia in decision-making. To this end, I review recent findings on decision inertia and subsume a generalized experimental paradigm to investigate decision inertia in a controlled lab environment. These conceptual foundations are necessary to isolate decision inertia from other interacting phenomena. I then illustrate the current state of the decision-inertia research and derive research hypotheses. In doing so, I discuss potential motivational and physiological drivers of decision inertia. These findings are generalized into a first research model to contribute to existing decision support design research. In the next step (Section 4), I investigate the cognitive foundations of decision inertia (laboratory evaluation). The foundations provide further insights into the nature of the drivers of this "reluctance to change". Based on the empirical evaluation, I generalize these findings and try to derive counter-methods to overcome decision inertia in a real-world scenario. I then continue in Section 5, presenting an implementation of a standardized decision inertia experiment and test wheter decision inertia can be reproduced in a laboratory setting. In the next section, a practical discussion of the findings and implications is provided. I conclude this work with an overview of the limitations of the studies, and I briefly make recommendations for future work.

2 Theoretical Background and Assumptions

Abstract. *Today, economists know that economic decisions do not always involve conscious or deliberate control by the self. There is increasing evidence that most decisions are made by automated, unconscious processes, or are based at least on an interaction of automated-intuitive and deliberative processes (see Alós-Ferrer and Strack (2014); Dhar and Gorlin (2013); Gigerenzer (2008); Kahneman (2003)). In this section I review the theoretical background of a paradigm: Generalized Dual-Processing Theories. Generalized Dual-Processing Theories are an established theoretical framework to understand and explain human decision-making anomalies like decision inertia, and decision-making in general. Consequently, this section builds the theoretical foundation for the experimental studies in Parts II and III. Furthermore, it provides a theoretical foundation for the Choice Architecture approach proposed by Thaler and Sunstein (2008), on which I rely on in the final Part III of my thesis.*

2.1 Generalized Dual-Processing Theories

Many researchers, have come to solutions to complex problems exactly at a time they were giving it no thought. For instance, the mathematician Henrie Poincaré reported finding the solution of a complex problem while entering a bus during an expedition, or it is said that Isaac Newton discovered the universal gravitation law, when he rested in an orchard and the famous apple fell on his head.

Unconscious processes are not only relevant to solving complex problems, and they occur during almost every moment in a person's life. Certainly one may recognise a spontaneous solution to a problem while playing sports, shopping or taking a shower. Unconscious processes are also triggered if one buys unneeded products at the supermarket (Rook, 1987), or if one remains comfortably lying on the couch and prefer to watch the new Netflix serial instead of exercising, for instance (Anderson, 2003). Today's judgement and decision-making researcher suggest this type of cognitive processes do "*not involve what we usually associate with the word thinking*" (Thaler & Sunstein, 2008, p.19).

For a long time, research in economics and judgement and decision-making did not take this type of cognitive processes seriously and followed the paradigm that decisions are made consciously and deliberately. In particular, traditional bounded-rationality research and economists have postulated that humans make decisions always deliberatively and are always capable of making rational decisions by comparing the costs and benefits of their decisions. Consequently, suboptimal decisions are assumed to be the result of missing information (Friedman, 2007, 1957), or because the actual solution is "satisfying" for the decision-maker (H. A. Simon, 1979). In particular, it has not been considered that suboptimal decisions could be formed systematically by intuitive, unconscious processes that follow specific rules and heuristics which contradict utility theory, violating what research has subsumed under the concept of "Rational Choice Theory" (Thaler, 1980).

However, judgement and decision-making research in the past three decades (Gawronski & Creighton, 2013), has started to target this shortcoming and reported a broad range of studies and tasks in which humans make decisions without processing them deliberatively, and furthermore behave systematically against their own interests (see Thaler and Sunstein (2008) for an illustrative overview of such kind of "irrational" decision anomalies). Numerous studies and theories generalizing and reviewing these findings of human judgement and decision-making have established that this happens because human judgement and decision-making is based on two different, and probably distinct cognitive components (Alós-Ferrer & Strack, 2014; Gawronski & Creighton, 2013). In particular, these studies share a common theoretical paradigm, often described as *Generalized Dual-Processing Theory*. This paradigm is a kind of expanded version of the Rational Choice Theory, which assumes one deliberative-rational mind, while Generalized Dual-Processing Theory postulates that two different and distinct types of cognitive processes form our behaviour and intentions (Thaler, 1980). Or in other words, the main contention of Dual-Processing Theory is that people rely on intuitive, unconscious impulses *and* on deliberative, conscious processes in decision-making.

Relying on this foundation, different domain-specific dual-processing frameworks have been proposed to explain decision anomalies across the domains, for instance in social psychology (Strack & Deutsch, 2004), consumer behaviour (Strack & Deutsch, 2006), auction theory (Adam, Krämer, Jähnig, Seifert, & Weinhardt, 2011), preference construction (Dhar & Gorlin, 2013), or as a general framework for economic decision-theory (Alós-Ferrer & Strack, 2014). All have in common that they link the two facets of decision-making, suggesting that individual decisions are the result of the interaction of different automatic, impulsive processes (e.g., intuitive decision-making) or reflective, controlled processes (e.g., deliberative decision-making) (Dhar & Gorlin, 2013; Alós-Ferrer & Strack, 2014).

In this Chapter, I follow common practice in judgement and decision-making, naming these two types of cognitive processes by their neutral terms *System 1* or intuitive processes, and *System 2* or deliberative processes (Alós-Ferrer & Strack, 2014; Gawronski & Creighton, 2013; Stanovich & West, 2000). Furthermore, I illustrate, the most relevant and popular dual-processing theories building the foundation for many other domain-specific processing theories. However, before I start discussing and reviewing the theoretical streams, I briefly illustrate the key idea of the dual processing paradigm and the interaction of System 1 and System 2 in more detail.

For that purpose I follow Kahneman (2003), using an example from the cognitive reflection tests from Frederick (2005). This test is an established measure of human self-monitoring, or the ability of System 2 to control System 1.

So please try to answer the following questions:

> *(1) A bat and a ball costs \$ 1.10 in total. The bat costs \$ 1.00 more than the ball. How much does the ball costs? …… cents*
> *(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100*

machines to make 100 widgets? ...... minutes
(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ...... days.
- adopted from Frederick (2005, p.27)

As I will illustrate, the cognitive reflection test is a revealing example of how the dominant System 1 can result in an intuitive, unconscious, fast, automatic but wrong answer (Kahneman, 2003). In the first case, the answer "10 cents" seems to be intuitively correct, probably due to the analogy that 1.10 can be separated easily in 1 and 0.10, which seems to fit the difference. However, the correct answer is 0.05 cents, which can also be illustrated by basic mathematical transformations:

$$ball + bat = 1.10 \tag{2.1.1}$$
$$ball + (ball + 1) = 1.10 \tag{2.1.2}$$
$$2 \cdot ball + 1 = 1.10 \tag{2.1.3}$$
$$2 \cdot ball = 0.10 \tag{2.1.4}$$
$$ball = 0.05 \tag{2.1.5}$$

System 1 is automatic and fast and can push you intuitively into a decision before System 2 can react. Most people feel so confident in the first idea that the ball must cost 0.1 and the bat 1.0 that they do not proof their first guess, and they give a fast but wrong answer. It has nothing to do with people's ability to solve a fifth grade calculation, the wrong answer is given because System 1 provides such a confident response that the slow System 2 has difficulties stopping it.

The same mechanisms are at work in the other questions (Frederick, 2005). In question (2) the intuitive answer seems to be 100 (5 minutes, 5 machines, 5 parts must result in 100 minutes, 100 machines, 100 parts). However, if the relationship that 5 machines produce in 5 minutes is linear, and consequently it would take 1 machine 5 minutes for 1 part, and 100 machines also 5 minutes for 100 parts and so on. The last question pushes you into intuitively calculating the growth rate, which normally results in the insight that you cannot compute it without pen and paper, and then you probably guess something between around the mean like 25 or 30. However the correct answer can be given by using the fact that the growth rate doubles every day. Consequently the pond will be half-covered one time step before it is fully covered, which is the 47th day. Again, the correct response is far from the intuitive one.

If we take a look at the study of Frederick, some sessions contained only about 5 % of participants that could answer this questions correctly (see e.g. Michigan State University or University Toledo, Frederick (2005)). Other studies report similar results, manifesting as a persistent inability of humans override their impulsive System 1 (see Brañas-Garza, Kujal, and Lenkei

(2015) for a review). This is interesting, because it illustrates across educational background that humans have a tendency to rely on quick judgements (Kahneman, 2003). This comes even more to the fore considering the question "A banana and a bagel cost 37 cents. The banana costs 13 cents more than the bagel. How much does the bagel cost?" (Frederick, 2005), has been answered correctly by far more participants. This discrepancy suggests that it depends on the strength of the impulse of System 1, and not on the cognitive abilities in statistical reasoning, whether or not humans rely on their intuitive processes.

Recent judgement and decision-making research explains this behaviour with dual-processing theory. The Generalized Dual Process Theories specify the characteristics and interaction of these two systems in the example. However, they are not related only to this kind of question, they are used as domain-independent theories of information processing (Strack & Deutsch, 2004). In recent judgement and decision-making research and related disciplines such as economics, dual-processing theories are used as an overarching theory to help in structuring and interpreting experimental results. For instance, Satpute and Lieberman (2006) report that they are successfully used in judgement and decision-making research to explain categorization (Murphy, 2002), memory (Squire & Zola, 1996), reasoning (Sloman, 1996), and decision-making under uncertainty (Kahneman, 2003). For that purpose, dual-processing theories draw their findings mostly from reviewing market anomalies in economics, or systematic violations of rational choice in judgement and decision-making. For instance, Kahneman and Tversky have generalized recent dual processing literature into a dual-processing model based on prospect theory to explain biased economic decision-making (Kahneman, 2003).

In Table 1, I list the most popular dual-processing theories in judgement and decision-making, and their related sources. For a comprehensive review, I refer to Smith and DeCoster (2000) discusses and compares existing dual-processing theories, or to Gawronski and Creighton (2013) provide a comprehensive overview of the development of Generalized Dual-Processing Theory. Furthermore, I would like to refer to Evans (2012), giving an elaborated overview of Generalized Dual-Processing Theory illustrating popular misunderstandings, false beliefs and fallacies about the usage and characteristics of this stream of research.

Table 1: Expanded overview of the most popular dual-processing theories adopted from Alós-Ferrer and Strack (2014), Stanovich and West (2000), and Evans (2008). The most popular theories, discussed in the next part of this Chapter are marked in bold.

Source	System 1	System 2
Schneider and Shiffrin (1977)	Automatic	Controlled
Chaiken (1980), Chen and Chaiken (1999)	Heuristic	Systematic
Epstein (2003, 1973)	Experiential	Cognitive or Rational
Evans (1989, 2006)	Heuristic	Analytic
Fodor (1983, 2001)	Input modules	Higher Cognition

Continued on next page

Table 1 – *Continued from previous page*

Hammond (1996)	Intuitive	Analytic
Nisbett et al. (2001)	Holistic	Analytic
Reber (1993), Evans and Over (1996)	Implicit or tacit	Explicit
Satpute and Lieberman (2006); Lieberman (2003)	X-system	C-system
Kahneman (2011, 2003)	System 1	System 2
Schneider and Schiffrin (1977)	Automatic	Controlled
Sloman (1996), Smith and DeCoster (2000)	Associative	Rule-based
Stanovich (1999, 2004)	System 1 (TASS)	System 2 (Analytic)
Strack and Deutsch (2006, 2004)	Impulsive	Reflective
Toates (2006)	Stimulus bound	Higher order
Wilson (2002)	Adaptive unconscious	Conscious

2.1.1 Cognitive-Experiential Self-Theory

While Kahneman and Tversky's dual-processing theory is generally accepted in recent judgement and decision-making research, initial contributions to this model have been in context of the cognitive-experiential self-theory (Epstein, 2003, 1973). This Cognitive-Experiential-Self-Theory (CEST) was introduced by Epstein. "Integrative" indicates that it has the claim to be a kind of *generalized* theory that can be applied to explain human judgements and decision-making regardless of domain.

The main assumption of Epstein's theory is the idea that cognitive processes can be organized in distinct structures (Epstein & Pacini, 1999; Epstein, 1973; Sarbin, 1952). This is opposite to the one-mind assumption. Following this rationale, Epstein suggests dividing the human self into an unconscious and a conscious system. These two systems are related to two different cognitive components, building the human understanding of the world, and forming human intentions.

Furthermore, Epstein assumes that knowledge is represented in different individual conceptions about the world, embedded in each of these two systems. These individual "reality-theories" about the world consist of different schemes that represent an individual's understanding and knowledge. These schemes can be characterized by their generalizability and stability (see Figure 5).

The so-called rationale system contains schemes that represent very general world-knowledge (e.g. I am human, or there exists a god in the world). This type of schemes is very stable, and cannot be manipulated or changed easily. The other type of schemes related to the experiential system is very situation-specific, and can be changed easily without influencing the stability of the personality (e.g. this brand of tooth-paste is a good one). These two types of schemes are organized hierarchically in the two systems. Epstein describes this in more detail in the following manner:

> *„According to CEST [Cognitive-Experiential Self Theory], people adapt to their environment by means of two information-processing systems: A preconscious experiential system and a primarily conscious rational system. The two systems operate in parallel and are interactive. The rational system operates through a person's understanding of logical rules of inference. The experiential system operates according to heuristic principles* (Epstein & Pacini, 1999, p.462).

Following this description, human judgement and decision-making can be modelled as an interaction of two distinct systems: an experiential system, and a rational system (see Figure 5).

Epstein has postulated that the *first component* (the experiential system) is based on preconscious perception and that it works associatively, quickly, and effortlessly (Epstein, 2008, 2003). The associative character is created by the automatic connection of similar, coherent and emotionally connected stimuli to a global context. Human experiences appear as nonverbal representations, metaphors, and narratives. The experiential system can make everyday decisions effortless and is related to emotional decision-making. The experiential system's processes are context-dependent, and manifest in concrete (emotional) pictures. Emotions and affect are influenced by these pictures and (re-)create these pictures. In his further work, Epstein extended these descriptions and linked the system to motivation and passion, and postulating that it is also the creator of creativity, humour, empathy and other soft skills (Norris & Epstein, 2006). Compared to subsequent analogous models of Dual-Processing Theories, Epstein's experiential system is more sophisticated and equally important than its counterpart: the rational system. Furthermore, it contains a wide range of knowledge and not only a number of unrelated "cognitive short-cuts" (see section 2.1.2).

The second component, the cognitive or rational system, is the human conscious system of thought. Epstein uses the word "rational" from a cognitive perspective. Particularly, to refer to analytical thinking, but rational outcome is always the optimal outcome (in sense of Bernoulli rationality, or normative rationality). The rational system is responsible for abstract and analytical thinking and abstract problem solving, which requires effort in the form of cognitive resources. The cognitive system acquires knowledge through deliberative information-processing and learning (e.g. from books or explicit sources of information) (Epstein, 2008). This system can also represent opinions, but the opinions do not come from associations, as in the experiential system, rather, they come from conscious learning and logical conclusions. In this way, the system can also learn from experience. Changes in the relations and structure of the cognitive system are abstract and context-independent. The adoption depends on the

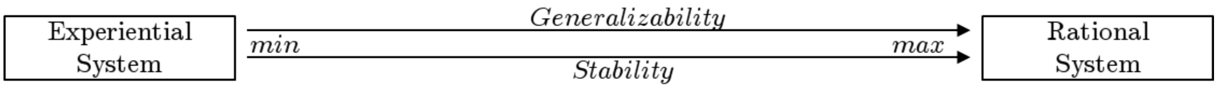

Figure 5: The relationship of the experiential and the rational system according to Epstein and colleagues: The experiential system has minimal generalizability and stability compared to the rational system; however, it remains very sensitive to context. Each system has a different perspective on a situation and builds the intention.

dominance of the stimuli and is more quickly processed than through the experiential system (Epstein, 2003). Furthermore, unlike the experiential system, it does not regard emotions, and it is assumed to be phylogenetically younger, due to its long-term thinking-style, which has probably evolved in more recent steps of human evolution.

The two systems are equally important and neither is superior. Epstein suggests that both work simultaneously and interact in both directions or influence each other. This interaction, illustrated in Figure 6, works as follows: The intuitive system results in an intuitive response, while the rational system generates a rational logical response. Our brain uses these responses to make a decision. The interaction of the systems is simultaneous and sequential. The experiential system reacts faster, but the rational system can suppress it or change the answer. If the rational system does not react, the response of the experiential system is automatically expressed. The advantage of the rational system is that it understands the experiential system, an understanding that the experiential system does not have of the rational system. On the other hand, the experiential system can influence the rational system without the rational system registering this influence. In consequence cognitive-experiential self-theory postulates that both systems are always involved in human decision-making and behaviour.

However, if the responses of the two systems are divergent or incongruent, a compromise must be found to solve the conflict between them. The solution of this conflict depends on the individual dominance of each response (response stumulus). Factors driving the dominance of the intuitive system for instance include emotional arousal, while the situational circumstance of the decision can increase the dominance of the rational system. Epstein suggests that the solution of this conflict is also responsible for biases in decision-making and for superstitious beliefs. This occurs in situations where our rational judgment and decision-making are overwhelmed by experiental and emotional processing. To understand this relationship more deeply, Epstein et al. developed a questionnaire (the so called Rational-Experiential Inventory) to measure inter-individual differences in the preference for the dominance of the two systems (Epstein, Pacini, Denes-Raj, & Heier, 1996).

Epstein also derived further different psychological scales to measure inter-individual differences in the characteristics and processing of the two systems, which predicted different aspects of human judgement and decision-making reliably and were independent from other popular predictive performance measures at this time like e.g., Intelligence Quotient (IQ) (Epstein, 2008). For instance, besides the popular *Rational-Experiential Inventory*, Epstein et al. has proposed the *Constructive-Thinking Inventory*, which measures inter-individual differ-

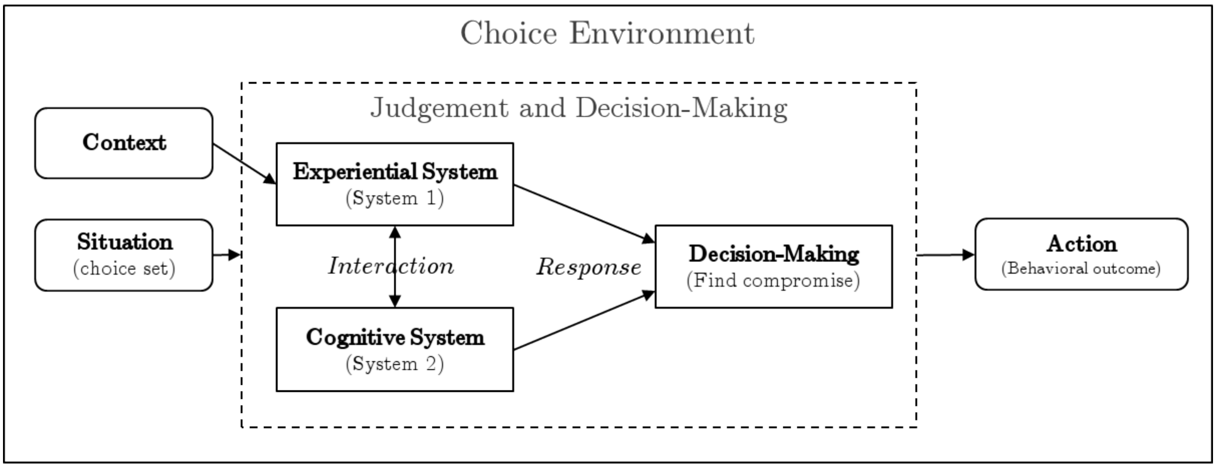

Figure 6: Epstein suggests that the two systems interact directly. System 1 considers the context in the decision-making and together with the generalized view of System 2 the intention is formed.

ences in the efficiency of the experiential system or intelligent problem-solving in everyday decisions (Epstein, 2008; Epstein & Meier, 1989).

The scales measure different aspects of constructive and non-constructive thinking (emotional coping, behavioural coping, categorical thinking, superstitious thinking, naive optimism, negative thinking, and global scale). The high correlation of the scale with success in other settings affirms the explanatory power of Epstein's theorization. For example, it could be shown that high scores in the Constructive-Thinking Inventory are not correlated with intelligence, but rather predict success in one's social life, work, mental adjustment and well-being better than does an intelligence test (Epstein, 2008; Scheuer & Epstein, 1997; Katz & Epstein, 1991; Epstein, 1992; Epstein & Katz, 1992). Subsequent judgement and decision-making research has provided evidence for the major assumptions of cognitive-experiential self-theory (see Epstein (2008) for a review), and it is established that Epstein's work laid a solid foundation for later generations of dual-processing theories.

Table 2: Overview of the key characteristics of the cognitive-experiential self-theory, based on Table 2.2 (Epstein, 2008, p.26).

Component	**Cognitive-Experiential Self-Theory**
Decision-making	Make a decision compromise based on the response from experiential and rational system
System 1	Preconscious, automatic, effortless, associative, affective, holistic, context-dependent
System 2	Conscious, deliberative, abstract, weighted arguments, affect-free, analytic, context-independent

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Table 2 – *Continued from previous page*

Measures	Rational-Experiential Inventory (Epstein et al., 1996), Constructive-Thinking Inventory (Epstein & Meier, 1989)

2.1.2 System 1 and System 2 Model

In a large series of papers Kahneman and Tversky have investigated human judgement and decision-making under conditions of uncertainty (e.g., Tversky and Kahneman (1973); Kahneman and Tversky (1972); Tversky and Kahneman (1971)). In particular, they have focused on situations in which subjects have violated the predictions of rational choice theory. For instance, the participants systematically violated their own preferences in their experiments, although they could have recognized they were doing so (Kahneman, Knetsch, & Thaler, 1991).

Kahneman and Tversky observed that these situations were surprisingly diverse and frequent, and that the effects were also stable on an inter-individual level. Furthermore, Kahneman and Tversky were surprised about the persistent discrepancy between statistical intuition and knowledge (Kahneman, 2003). Regardless of the statistical knowledge, experts and normal decision-makers showed the same systematic deviations from rationality in statistical decision-making tasks.

Consequently, Kahneman and Tversky have puzzled over how to explain such behaviour. To explain the numerous studies building on their work and reporting systematic violations of Rational Choice Theory, Kahneman and Tversky generalized their findings in the "two system model" of human judgement and decision-making (Kahneman, 2011, 2003). The main paradigm of their model, as in other dual-processing theories such as CEST, is that they distinguish between two processing modes of human judgement and decision-making, encapsulated in two cognitive systems (Kahneman, 2003).

Kahneman termed these two different systems, *System 1* and *System 2*, and describes their characteristics as follows:

> *„The operations of System 1 are typically fast, automatic, effortless, associative, implicit (not available to introspection), and often emotionally charged; they are also governed by habit and are therefore difficult to control or modify. The operation of System 2 are slower, serial, effortful, more likely to be consciously monitored and deliberately controlled; they are also relatively flexible and potentially rule governed"* (Kahneman, 2003, p.698).

Kahneman and Tversky wanted to reduce the complex debate about the naming of the system and the related discussions about their functionalities. They wanted to give a short, sharp and significant term for these types of decision-making to make the terms more usable for economic modelling. Hence, they simply decided to name these two systems "system 1 and system 2" (Kahneman, 2011). The first can make fast, automatic, and effortless decisions. Because these properties are also associated with intuitive decision-making which can be observed in animals, the decision-making of this system is also related to affective processing. These effects of system 2 can support heuristic processing. Other sources of simplified, and effortless decision-making like habits and routines are not part of this system, but they influence its behaviour (e.g., emotions that drive the output of system 1 can be suppressed by routines). System 1 processes all input from the human senses like a filter. It is able to detect outliers (relevant events) in a big stream on input data. This processing is always active and it cannot be "shut-down" willingly. Kahneman postulates that system 1's knowledge is based on experiences and associations. These sources of knowledge are easy to process connected to emotions an individual's past. As a consequence the knowledge expressed by this kind of associative representation, is modified or trained very slowly and follows no general logic (Kahneman, 2003).

The conscious system 2 receives input from system 1. Compared to system 1, system 2 processes information slower, and requires more effort of the individual. System 2 processing is deliberative. The individual processes it consciously and relies on facts represented by rules, considerations or trade-offs. While the system 1 can process much information in parallel, due to the complexity of the knowledge base and processing, system 2 is a serial processing system. Starting other processes decreases the effectiveness of system 2, because of its serial processing characteristic. Hence, system 2 is only rarely activated otherwise it runs at low-energy. Kahneman and Tversky postulate that System 2 can place very high demands on cognitive resources. For instance, many people can remember a time in their childhood when they tried to solve a complex mathematical problem, and failed to notice basic events in their surroundings, such as the doorbell ringing. Kahneman and Tversky explain such situations in the following manner: system 2 consumes so much cognitive resources that the brain could not run certain system 1 processes (e.g., recognising thering of the door bell). Compared to system 1, system 2 thinking is perceived by decision-makers as controlled, conscious decision-making. Another feature of system 2 is that it can also partly influence or control some system 1's activities, such as breathing, emotional responses or reflexes. However, the initation of system 2 processing is also very sensitive to distraction (Kahneman, 2003). Most people know, how difficult it can be to solve difficult cognitive tasks in noisy environments. On the other hand, system 1 processes relying on associations are not influenced so easily.

As Figure 7 illustrates, Kahneman differentiates between content and processing of human judgment and decision-making. He argues that system 1 is related to human perception at the level of processing perspective. Both are fast and associative. Systems 1 and 2 have a kind of long-term knowledge base that influences decision-making. His theory suggests that system 1 the perceptions of situations are processed similarly. A relevant further difference is that system 1 relies on concepts or perceptions that generate impressions or non-voluntary decisions, while system 2 can make judgements or voluntary decisions (Kahneman, 2003). As a consequence, deliberative processes or what judgement and decision-making researchers term *thinking*, is located in the system 2. Hence, without an activation of system 2, deliberate

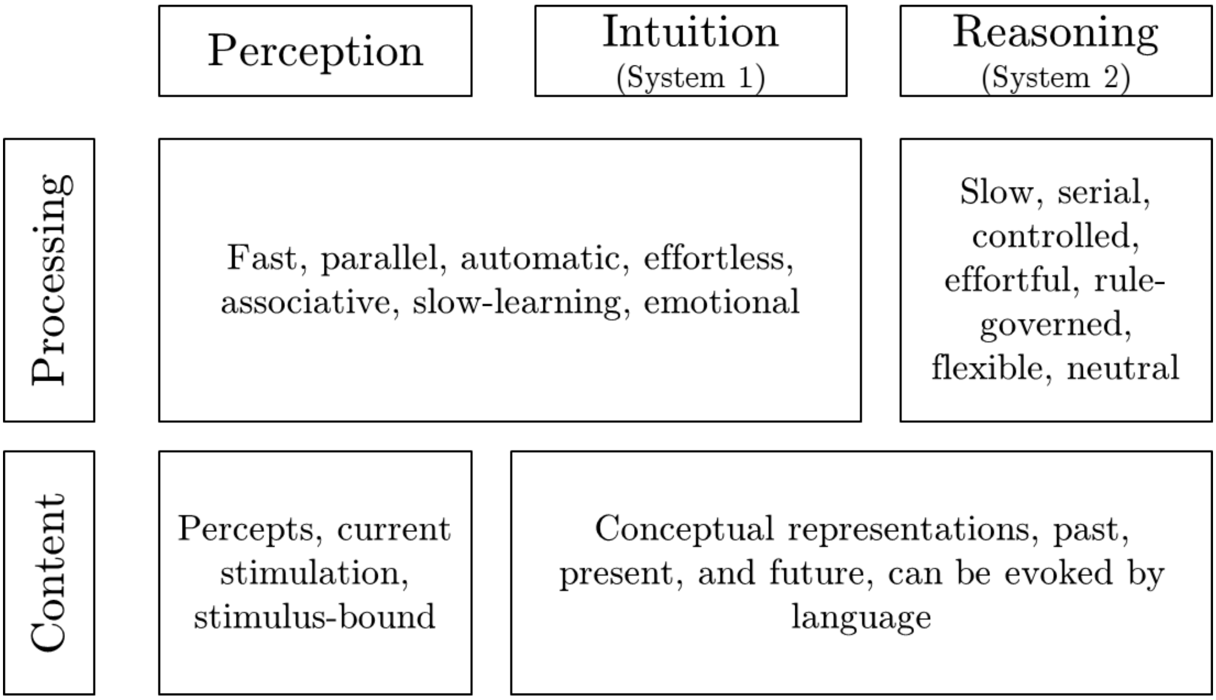

Figure 7: A descriptive overview of the key characteristics of the dual-process theory of Kahneman and Tversky, with the two levels process and content (Kahneman, 2003, p.698).

reasoning is not possible.

Now that the characteristics of the two systems have been presented, the question of interaction and actual decision-making remains open. Kahneman and Tversky (Kahneman, 2003) postulate that decision-making happens in several steps (see Figure 8). The impulsive response of system 1 is monitored by system 2. If system 1 does not recognize a pattern in the input stimuli from the choice set, system 2 gets activated. Otherwise, system 1 generates a fast and automatic response. This automatic response can be correct, or it can be so fast that system 2 does not activates before the subsequent behavioural response of the decision-maker. If the system 2 has enough processing time and can recognize an error in the response of system 1, it overrides or adjusts the response of system 1. This adjustment or override occurs because the decision-maker does not want to rely on emotions, feelings, or heuristics. System 2 can adjust system 1 due to missing information in the response of system 1 or when it recognizes that system 1 makes biased decisions.

Kahneman and Tversky have focused in many laboratory studies on economic decision-making it therefore poses the question of how this model can now also complement and support experimental research. In particular, it would be an important contribution to be able to measure the interaction of the two systems in order to better understand and explain decision-making behaviour. In order to fulfill these requirements, Kahneman and Tversky propose different approaches in their studies. They propose using the facts that the mental capacity of system 2 is limited, and that its processing is serial. Processes in system 1 are effortless, and can be combined with other tasks (Kahneman, 2003; Pashler & Sutherland, 1998; Kahneman, 1973). If biases occur only through combining decision-making with other tasks, the source of the bias

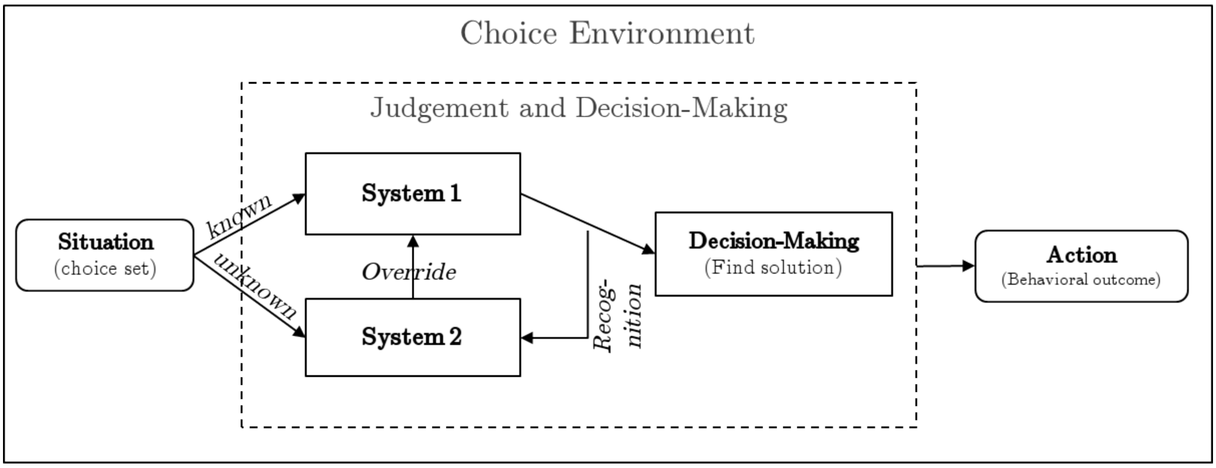

Figure 8: The *system 1 and system 2 model* of human decision-making according to Kahneman. System 1 gives a fast response, which can be overwritten by a slow response of system 2. Decision-making is the result of the interaction of the two cognitive systems.

is probably system 2, and vice-versa. To measure the activation of system 1 and system 2, or to identify the source of a decision, Kahneman further proposes measuring bio-physiological responses like arousal or pupil sizes, which expand in system 2 processing (Kahneman, 2011). However, a fully-agreed upon and standardized methodology for such measurements does not yet exist in judgement and decision-making research.

Table 3: Overview of the key characteristics of the system 1 and system 2 theory, based on Kahneman (2003).

Component	**Cognitive-Experiential Self-Theory**
Decision-making	Decisions made by uncontrolled impulsive response (system 1), or deliberatively based on system 2
System 1	Fast, parallel, automatic, effortless, associative, slow-learning, emotional
System 2	Slow, serial, controlled, effortful, rule-governed, flexible, neutral
Measures	Combine decision-making with other tasks (Kahneman, 2003; Pashler & Sutherland, 1998; Kahneman, 1973), bio-physiological responses (arousal, pupil size) (Kahneman, 2011)

2.1.3 Reflection-Reflexion-Model

In the previous sections, I introduced two popular generalized dual-processing models: The *cognitive-experiential* self-model, which draws its evidence from studies reporting the high explanatory power of the rational-experiential inventory and constructive-thinking inventory (see Section 2.1.1), and the *system 1 system 2 model* of Kahneman and Tversky, which draws its evidence from laboratory studies on decision-making under uncertainty. Another model, provides further evidence from a third methodological perspective: The *reflection-reflexion model*, based on neurological studies of human judgement and decision-making (Satpute & Lieberman, 2006; Lieberman, 2003).

Other dual-processing theories like the reflection-reflexion model assume that humans make decisions based on several judgemental processes organized into two systems, but link these different systems to specific areas in the human brain. Lieberman conceived the reflection-reflexion model to target the shortcoming of existing dual-processing theories, which always differ between automatization and control, which he assumes to be a "shopworn concept" (Lieberman, 2003, p.4). He expands the previously discussed models and findings, and contributes to existing dual-processing research, because previous models have not considered the neural bases of decision-making (Satpute & Lieberman, 2006). In particular, his model explains more deeply when the systems are activated by discussing the consequences of the permanent activation of the X-system. Lieberman underlines these assumptions of neural representations of the two systems in the human brain:

> *„We will describe the phenomenological features, cognitive operations, and neural substrates of two systems that we call the X-system (for the X in reflexive) and the C-system (for the C in reflective). These systems are instantiated in different parts of the brain, carry out different kinds of inferential operations, and are associated with different experiences"* (Lieberman, 2003, p.4).

Lieberman's dual-processing model, differentiates between an X-system, which can be compared to system 1 processes (automatic/intuitive) of other dual-processing theories, and a C-System that can be compared to the type of system 2 processes (conscious or deliberative). The X-system is a parallel processing system. Processed patterns are matched to patterns from knowledge. These patterns are used as links. This linkage results in a continuous stream of consciousness, or what humans perceive as the "world outside" (Lieberman, 2003). X-system's components are characterized as faster in processing than the C-system, but slower in adoption. Its processing is faster because its structure allows parallel processing. The processed thoughts and knowledge are unconscious, what Lieberman terms "implicit semantic associations". If the X-system has a problem or if a specific situation occurs, an alert is triggered and the C-system gets activated.

The C-system is responsible for deliberative judgement and decision-making. It works serially, uses symbolic logic, and it can react only on input from the X-system. Also Lieberman assumes that the X-System is phylogenetically older. The C-system is highly adaptive, but slow in processing. This processing style is perceived as an "internal linguistic monologue" (Satpute & Lieberman, 2006). Due to the costly or resource-consuming processing style, it is easily at its maximum capacity. As a consequence, it is activated only when it is necessary, or from an evolutionary perspective, it is sparingly used to save energy.

Table 4: Overview of the key characteristics of the two systems and their related brain areas, based on the reflection-reflexion model.

X-System	C-System
Orbitofrontal cortex	Lateral prefrontal cortex
Basal ganglia	Medial temporal lobe
Amygdala	Posterior parietal cortex
Lateral temporal cortex	Rostral anterior cingulate cortex
Dorsal anterior cingulate	Medial prefrontal cortex
	Dorsomedial prefrontal cortex

In the reflection-reflexion model, distinct brain areas (see Table 4) are linked to the two systems of judgement and decision-making. The brain areas linked to the C-systems are the medial temporal lobe, posterior parietal cortex, rostral anterior cingulate cortex, and lateral prefrontal, medial prefrontal, and dorsomedial prefrontal cortices (Satpute & Lieberman, 2006). In general, these brain areas have been linked to analytical thinking and decision-making in related magnetic resonance imaging studies. For instance, the lateral prefrontal cortex has been associated with reasoning and logic (Noveck, Goel, & Smith, 2004), and with mathematical problem-solving (Prabhakaran, Rypma, & Gabrieli, 2001), and related cognitive processes (Prabhakaran et al., 2001, p.90).

The brain areas related to the X-system are the amygdala, basal ganglia, ventromedial prefrontal cortex, dorsal anterior cingulate cortex, and lateral temporal cortex (Satpute & Lieberman, 2006). These brain areas are related to emotional and unconscious processing. For instance, neuro-science studies have linked the amygdala to reward and emotional cognition (Adolphs, Tranel, & Damasio, 1998). Lieberman and Satpute discuss that these properties of the amygdala could trigger the C-system based on personal traits (based on genetics or experiences) due to a reaction of fear (Satpute & Lieberman, 2006).

Independent of judgement and decision-making, the X-system streams continuous thoughts based on pattern matching in the lateral temporal cortex based on the information and knowledge in the C-system. In the reflection-reflexion model both systems are responsible for information processing, but compared to other dual-processing models, it is assumed that they do not directly interact (see Figure 9). Instead the X-system can activate the C-system via an alert stimulus; the C-system then tries to make a decision analytically or to solve the problems of the X-system. The C-system tries to solve this conflict, which can be influenced by cognitive load and motivation (Satpute & Lieberman, 2006). In doing so the C-system provides new information to the X-system to solve the conflict.

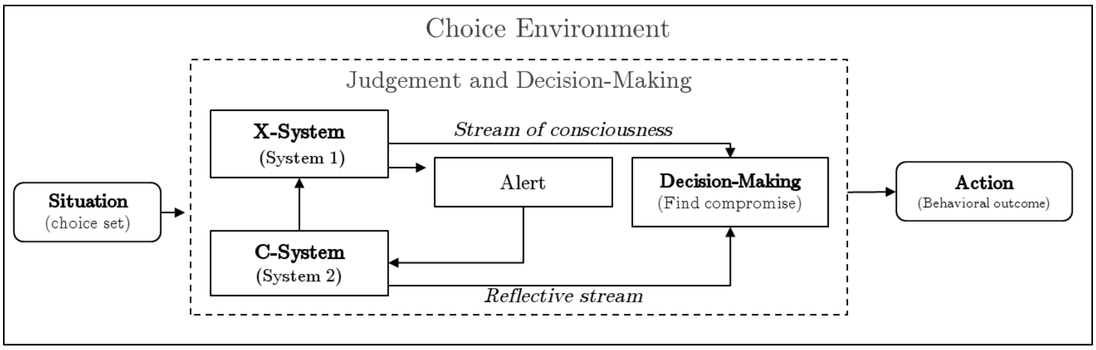

Figure 9: The two systems with their related brain areas based on Satpute and Lieberman (2006).

Because the two systems are in different brain areas, they can be activated at the same time. In particular, their working in parallel might cause processing conflicts that must be solved by finding a compromise between the different stimuli by processing them deliberatively. Lieberman and Satpute have argued that the C-system is activated only if the X-system alerts it (2006). However, the C-system can set activations in the knowledge base of the X-system. This kind of marker becomes activated under specific conditions allowing the C-system to control the X-system indirectly, even when it is not active.

As illustrated in Figure 9, the reflection-reflexion model follows the same structures as previous dual-processing theories. However, it is an outstanding characteristic of this model that it explicitly links the cognitive with the neural. The identification of specific brain areas linked to biased or rational decision-making could help to get a better understanding of suboptimal decision-making. As a consequence, this could help to identify biases at the moment they occur. The discussed areas are mainly linked based on theory, and an empirical proof for some of the relationships is still pending. However, Liberman and Satpute argue that "it is unlikely that this model has seen the end of its evolution. It should be taken as a working model rather than a finished product" (Satpute & Lieberman, 2006, p.88).

Table 5: Overview of the key characteristics of the reflection-reflexion model.

Component	Cognitive-Experiential Self-Theory
Decision-making	Decisions made by X-system based on information from the C-system, which is activated by alert triggers
System 1	Parallel-processing, fast operating, slow learning, cognition based on pattern matching, susceptible to associative biases
System 2	Serial processing, slow operating, limited by cognitive abilities, fast learning, susceptible to distraction

Continued on next page

Table 5 – *Continued from previous page*

Measures	Neural correlates (Satpute & Lieberman, 2006), see Table 4

2.1.4 Reflective-Impulsive-Model

The previous part, raises the need to find an overarching model integrating the different perspectives and approaches. Following this rationale to focus on the integration of the different dual-processing theories and models, the reflective-impulsive-model of human judgement and decision making has been proposed (Strack & Deutsch, 2006, 2004). The reflective-impulsive-model evolved mainly in a series of two related papers of Strack and Deutsch (Strack & Deutsch, 2006, 2004). Based on research in consumer and social psychology, the authors reviewed findings from cognitive psychology to integrate the different predictive aspects of existing dual-processing frameworks. For that purpose, they postulated ten theses summarizing the key characteristics of their model, which are generalizations of existing dual-process models and findings from cognitive psychology.

The foundation of these theses is the assumption, as in other dual-processing theories, that two type of processes are organized in two different systems in the human brain, and that they follow different operating principles (Strack & Deutsch, 2004). Finally, human behaviour is considered to be the result of a joint function of these two systems:

> *"Basic assumption. Social behaviour is the effect of the operation of two distinct systems of information processing: a reflective system and an impulsive system. The systems can be specified by different principles of representation and information processing."*(Strack & Deutsch, 2004, p.222).

According to Strack and Deutsch, these two systems differ in the way they produce a behavioural response. The reflective system results in an intention that activates behavioural schemes, while the impulsive system results in a spreading activation. The latter is a kind of unconscious reflex, processed without intention. While the main purpose of the reflective system is active and conscious thinking and reasoning, the impulsive system relies on the hedonistic principle of avoiding negative experiences and increasing positive stimulation (Strack & Deutsch, 2004, p.241).

The impulsive system continuously processes new information, what people perceive as continuous stream of consciousness, while the reflective system is active only when it receives a salient input (based on intensity and attention level), or when the impulsive system or the behavioural outcome prompts an error in the decision-making. As a consequence there are two ways of decision-making: Both systems work in parallel, or the impulsive system works alone (Strack & Deutsch, 2004).

Considering the knowledge base of the two systems, the impulsive system operates with input from an associative network (all associations built by experiences by the individual), and the current motivational focus of the individual. This so-called associative store, provides numerous schemes and associations as an input for decision-making. For instance, if a consumer sees fruits on a packaging, the associations "healthy" or "fresh" are automatic associated with the packaging. The other system, the reflective system, uses factual and value-associated knowledge. It works on a sub-symbolic level, and uses pattern-matching and symbolic procedures. It compares the perceived patterns with patterns from memory, for instance remembering that a fruit symbol does not mean that something is healthy. The reflective system prescribes that instead the ingredients like sugar or fat should be compared, and provides this information. Furthermore, the reflective system can add relation or "knowledge" into the associative store, which provides the associative links for the impulsive system. Elements that are linked in the reflective system can be also linked in the impulsive system. However, both knowledge representations are encoded in the neural network of the brain, and consequently the differences are on a computational level (see also Section 2.1.3).

Another relevant aspect is that the two systems have different processing capacities. The impulsive system is very fast, and it places only very low demands on cognitive resources. On the other hand, the reflective system requires high cognitive capacity, and as a result different reflective processes can work only serially and not in parallel. Furthermore, the capacities of the reflective systems are sensitive to high or low levels of arousal, hence different levels of arousal influence the interaction of the two systems, and the subsequent decision-making (Strack & Deutsch, 2004, p.223). In particular, in judgement and decision-making research, there is increasing evidence that the influence of the reflective system is reduced by arousal (Strack & Deutsch, 2004). For instance, in psychological research, arousal has been linked to simplified heuristic or stereotypic decision-making (Bodenhausen, 1993). Studies report a direct association between arousal and intense indoctrination (Baron, 2000), or in financial decision-making in electronic markets (Adam, Krämer, & Müller, 2015).

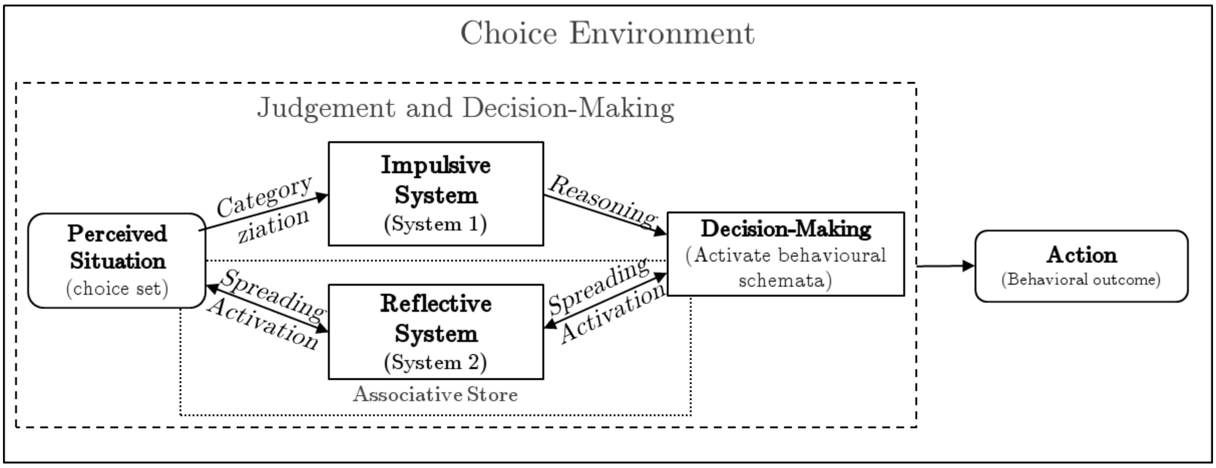

Figure 10: The *reflective-impulsive-model* of human decision-making according to Strack and Deutsch.

The interaction of the two types of processes (as illustrated in Figure 10) is described in the following manner: Firstly, the impulsive system activates different associations or associative clusters in the associative store based on the input it receives. Even if the processing is unconscious, it may result in different feelings "without syllogistic processes of inference" (Strack & Deutsch, 2004, p.224). The reflective system is activated if the behavioural schemata of the impulsive systems are in conflict with each other or with the situation. An example of such a situation is as follows: One schemata proposes to run away, while another schemata proposes to sit down, and calm down. The solution of this process conflict is computed by comparing the strength of the different schemata. If the activation of the schema of the impulsive or the reflective system reaches a specific threshold, the behaviour is activated (Strack & Deutsch, 2004, p.229).

Table 6: Overview of the key characteristics of the reflective-impulsive theory, based on Strack and Deutsch (2004).

Component	**Reflective-Impulsive-Model**
Decision-making	Decisions are made continuously by an impulsive system, or deliberatively based on the reflective system
System 1	Fast, parallel, effortless, associative
System 2	Slow, serial, effortful, reflective
Measures	Manipulating or measuring individual’s arousal as an approach to measure the influence or activation of the two systems (Strack & Deutsch, 2004, p.223)

2.1.5 Dual-Processing in Decision-Making Research

In a series of studies investigating dual-processing, various characteristics have been identified and associated specifically with the two systems. system 1 processing is generally described as automatic or impulsive, while system 2 processing is mostly described as deliberative. In the next section, I generalize the findings from the previous sections, and present and illustrate the most relevant characteristics that have been identified across current dual-process theory research to provide a common groundwork for the subsequent studies. Based on the suggestion of Evans (2008), I organize these associated attributes of the two kind of cognitive systems according to four groups of characteristics: *consciousness, phylogenetics, processing*, and *capacities* (as in Table 7).

The first group of attributes associated with dual-processing can be summarized under the context of cognitive *consciousness* of decision-making (Evans, 2008). Decisions made through of system 1 processing are mostly the result of automatic, effortless, and fast processes. On the other side, system 2 processing is characterized as controlled, effortful, and slow. This difference, can be illustrated by the analogy of a child learning to ride a bicycle. The automatic system starts without knowledge or intuitive associations and rules in this activity. System 2 will probably try to understand each movement and compute the correct behaviour by considering all information consciously. However, that approach will consume much cognitive capacity and the learningprocess itself will be very slow. Hence, the child experiences this phase as very difficult. However, after some time the child's system 1 will have learnt some simple heuristics and reflexes to handle the bike. These processes are unconscious and effortless, and through them, biking becomes an easy activity. Such examples do not illustrate that the outcome of one type of processing is worse or less useful, however. For instance, many scenarios exist in which automatic decision-making can save a person's life (consider a car accident, where one must decide how to behave without time to consider all consequences), and much evidence is available that system 1 allows us do stupid things (see Kahneman (2011), for a review). Recent evidence from cognitive psychology suggests that the two types of processes can overlap, for instance that system 1 processes can be partially built by intention and automation (Bargh, Gollwitzer, Lee-Chai, Barndollar, & Trötschel, 2001).

The second group, includes *phylogenetic* attributes of dual-processing (Evans, 2008). The main idea of most dual-processing theories is the assumption that the system is phylogenetically older than the cognitive structures of system 2. It is assumed that humans share this part with animals. However, this aspect has recently received much criticism in judgement and decision-making research, because the human mind evolved as a whole, and it may not be comprised of one distinct system that has evolved due to a single evolutionary process (Evans, 2008, p.259). Furthermore, there is evidence that humans share with chimpanzees certain system 2 characteristics (e.g. high-order mental representations; Whiten (2000); Evans (2008)).

A *a third group* of attributes can be classed as *processing* or functional characteristics (Evans, 2008). Decisions based on System 2 are described as serial-processing, abstract or reflective. However, that System 1 is parallel-processing, concrete, and non-reflective is not a contention shared by all dual-processing theories (Evans, 2008, p.261). For instance, speaking in one's mother tongue is based on system 1, while speaking a foreign language, requires use of system 2 (Thaler & Sunstein, 2008, p.20). In the first case, humans rely on fast and intuitive rules of thumb (e.g., what feels right), and in the second, humans rely on systematic grammar and rules learnt in language classes. Rule-based speaking is slow, exhausting, and strenuous, so people do not like to use it very much. They may even lose the desire for the other language quite quickly. Consequently, dual-processing models suggest that people should try to activate system 1 and to rely more on intuitive processes in speaking, or integrating another language into everyday activities. However, humans cannot always train themselves to learn intuitive rules that rely on system 1 to make a system 2 processes less taxing. Moreover, slow, sequential or rule-based processing is something that can also happen in system 1 processing. For instance, an impulsive response can be sequentially processed. Fortunately, though, this argument does not work in reverse. A wide range of evidence supports system 2 processing as mostly characterized by the attributes in Table 7, allowing us to separate these two kinds of cognitive systems. In other words, it can be assumed that System 2 processing is slow, but it cannot be assumed that every exhausting, slow decision is based on system 2.

The last group of attributes describes the *capacities* or individual differences of dual-processing

(Evans, 2008). For instance, some studies suggesting an association with System 2 processing and general intelligence (Stanovich & West, 2000; Evans, 2008). Others suggest that System 1 is related to affective or emotional decision-making. Furthermore, a relevant distinction in this area is "that between measures of cognitive capacity and dispositional thinking styles" (Evans, 2008, p.262). These conceptualizations target differentiating the cognitive or what decision-makers are cognitively capable of, and the motivational, or what they are motivated to do.

Table 7: Overview of the characteristics of the dual-processing theory processes.

Type 1 Process	**Type 2 Process**	**Sources (Selection)**
Category 1 *Consciousness*		
Preconscious	Conscious, self-aware	Epstein (2008), Kahneman (2003), Strack and Deutsch (2004)
Experienced passively and preconsciously	Experienced actively and consciously	Epstein (2008)
Implicit	Explicit	Epstein (2008)
Automatic	Deliberative, controlled	Epstein (2008), Kahneman (2003), Strack and Deutsch (2004)
Effortless	Effortful	Kahneman (2003), Strack and Deutsch (2004)
Slow learning, resistance to change	Fast learning	Epstein (2008),Kahneman (2003), Satpute and Lieberman (2006)
Fast	Slow	Kahneman (2003)
High capacity	Low capacity	Satpute and Lieberman (2006), Strack and Deutsch (2004)
Default Process	Inhibitory	Evans (2008)
Holistic	Analytic	Epstein (2008)
Category 2 *Phylogenetics*		
Phylogenetic older	Phylogenetic younger	Satpute and Lieberman (2006)
Evolutionary rationality	Individual rationality	Evans (2008)

Continued on next page

Table 7 – *Continued from previous page*

Shared with animals	Uniquely human	Satpute and Lieberman (2006)
Nonverbal	Linked to language	Evans (2008)
Modular cognition	Fluid Intelligence	Evans (2008)
Category 3 *Processing*		
Associative	Cause-and-effect relations, deductive	Epstein (2008), Kahneman (2003), Strack and Deutsch (2004),Thaler and Sunstein (2008)
Outcome-oriented	Process-oriented	Epstein (2008)
Intention activation	Spreading activation	Strack and Deutsch (2004)
Mediated by “vibes” from past experience	Mediated by conscious appraisal of events	Epstein (2008)
Categorical thinking	Nuanced thinking	Epstein (2008)
Organized in part by cognitive-affective modules	Organized in part by cross-situational principles	Epstein (2008)
Self-evidently valid: "Experiencing is believing"	Requires justification via logic and evidence	Epstein (2008)
Parallel-processing	Serial processing	Kahneman (2003), Satpute and Lieberman (2006), Strack and Deutsch (2004)
Non-reflective	Reflective	Satpute and Lieberman (2006)
Symmetric knowledge relations	Asymmetric knowledge relations	Satpute and Lieberman (2006)
Knowledge in form of common cases	Knowledge in form of special cases	Satpute and Lieberman (2006)
Concrete	Abstract	Epstein (2008), Satpute and Lieberman (2006)
Continuous	Specific (after alert)	Satpute and Lieberman (2006)
Skilled	Rule-following	Thaler and Sunstein (2008)
Category 4		

Continued on next page

Table 7 – *Continued from previous page*

Capacities		
Universal	Heritable	Evans (2008)
Associated with affect or emotions	Affect-free	Epstein (2008), Kahneman (2003)
Independent of general intelligence	Linked to general intelligence	Evans (2008)
Independent of working memory	Limited by working memory capacity	Evans (2008)

In summary, the research has been unveiled numerous properties associated with the two types of processes. The differences occur on four conceptual levels, and they describe how the two systems work together. They also allow conclusions to be drawn about the functioning of our brain, or they allow researchers to design experiments and to identify situations in which a specific type of process is preferred. Although most dual-processing approaches ascribe great importance to both systems, it is generally accepted that System 2 is rarely active in contrast to System 1. However, this asymmetry has serious implications for judgement and decision-making research, because "we often make mistakes because we rely too much on our automatic system"(Thaler & Sunstein, 2008, p.21). Much research in judgement and decision-making research has focused on understanding the driving factors across situations and domains. However, the interaction of both systems and the role of System 1 is a promising path to fully understand the numerous decision anomalies in when, why, and how decision-makers act against their own interests in judgements and decision-making.

2.2 Biases, System Conflicts and Divergent Processes

While for many years economic judgement and decision-making research has assumed that deviations from rationality are purely accidental (see Rational Choice Theory) or occur due to lack of information (see Herbert Simon's Bounded Rationality Theory), it was one of the two central contributions of dual-processing literature to show that a large part of human errors and mistakes are by no means accidental, but that these deviations from rationality are systematic. And secondly, that these systems can be explained by the duality of human decision-making (duality of system 1 and system 2).

In the next step, I examine the interaction of the different systems and how this interaction can result in biased decision-making, compared to situations where people behave rational. In particular, I discuss what happens if these two types of systems result in different outcomes, and how such a conflict can be solved - and on the other hand, what happens if it is not solved.

At present, one may assume that the system conflicts and the resulting biases are relatively robust, and that they are mostly independent of the cognitive abilities (Stanovich & West, 2000).

For instance, Daniel Kahneman reports that he was able to reproduce his experiments on representativeness heuristics (Tversky & Kahneman, 1971) at a conference of the Mathematical Psychology Society and the American Psychological Association (Kahneman & Frederick, 2002). Both are conferences where one might intuit that many humans with good mathematical abilities are present, and that they should not fall for these simple decision traps. Although calculations were so simple that they could have been calculated without problems on the questionnaires, numerous participants relied on intuitive, but false guesses to estimate probabilities (Kahneman & Frederick, 2002). This initially unintuitive finding led Daniel Kahneman and Amon Tversky to a series of follow-up studies, which inspired further researchers to get to the study these biases (see section 2.1.2).

Since the first studies of heuristics and biases, research in the 1970's, numerous biases have been identified, and described. For instance, a review of cognitive biases in decision support systems identified 37 potential relevant biases for information system design (Arnott, 2006). Another more general review identified up to 76 cognitive biases in the judgement and decision-making literature (Carter, Kaufmann, & Michel, 2007). Although some of the identified biases may overlap conceptually, it still shows the susceptibility of the human brain to rely on systematic decision errors.

A recent, crucial contribution to this research stream was made by Richard Thaler and Cass Sunstein. They gathered and reviewed these findings of heuristics and biases research, and they developed a theoretical framework to use these anomalies of human decision-making to improve our health, wealth, and even happiness (2008). This theoretical framework termed *Choice Architecture*, is presented in the last part of the following chapter, regarding the fact that biases can be reduced or debiased by decision support system design based on choice architecture (see e.g. Arnott (2006)).

Considering the findings of Section 2.1, it is generally accepted that the interaction of automatic system 1 processes and controlled system 2 processes constitute our intentions. These two kinds of processes can work together or against each other, and hence can result in different responses (for an overview, see Gawronski and Creighton (2013), B. K. Payne and Bishara (2009), B. K. Payne (2008)). Consequently, the processes of system 1 and system 2 can be *convergent*, pushing the decision-making towards the same behavioural response. However, they can also be *divergent*, meaning that they produce different responses. This kind of relationship of divergent and convergent processes, has also been called *compatible* and *incompatible* (Gawronski, Deutsch, LeBel, & Peters, 2008), or *conflicting* and *aligned* (Alós-Ferrer et al., 2016) in judgement and decision-making research.

It is assumed that errors or suboptimal decision anomalies occur, because one of the two systems produces a dominant behavioural response that is erroneous. In most cases of suboptimal decision-making, people rely on the response of our automatic System 1, even when our controlled system 2 indicates the opposite (Thaler & Sunstein, 2008, p.21). In other words, it might be that system 2 produces the correct response, but the response of the other system is too strong or too fast, and people rely on the wrong behavioural response. A typical situation would be that decision-maker intuitively decides to eat delicious cake as dessert, but at the checkout realizes that the decision was wrong (e.g., because system 2 recalling diet plans).

A possible method to model the interaction of the two types of cognitive processes and to understand erroneous decision-making is the control-dominating process dissociation approach (Lindsay & Jacoby, 1994; Jacoby, 1991). This approach relies on existing dual-processing theories, assuming that the interaction of the two systems can be modelled and visualized explicitly. In the first version (Jacoby, 1991), system 2 processes are assumed to be dominant and to easily override the outcome of system 1. If there is no response of system 2 or no strong response (e.g., if system 2 failed to compute a correct response), System 1 gives a single response.

To investigate this interaction of the two systems, the control-dominating process dissociation model recommends the usage of processing trees (Gawronski & Creighton, 2013). Processing trees (see Figure 11) are a theoretical expansion of dual-processing theory. They are "tools (a) for measuring the cognitive processes that underlie human behaviour in various tasks and (b) for testing the psychological assumptions on which these models are based" (Erdfelder et al., 2009). Consequently, they give a visual representation of the latent dynamic interaction of the two processes, and illustrate how the different responses result in a behavioural response (see Erdfelder et al. (2009), or Batchelder and Riefer (1999) for a review).

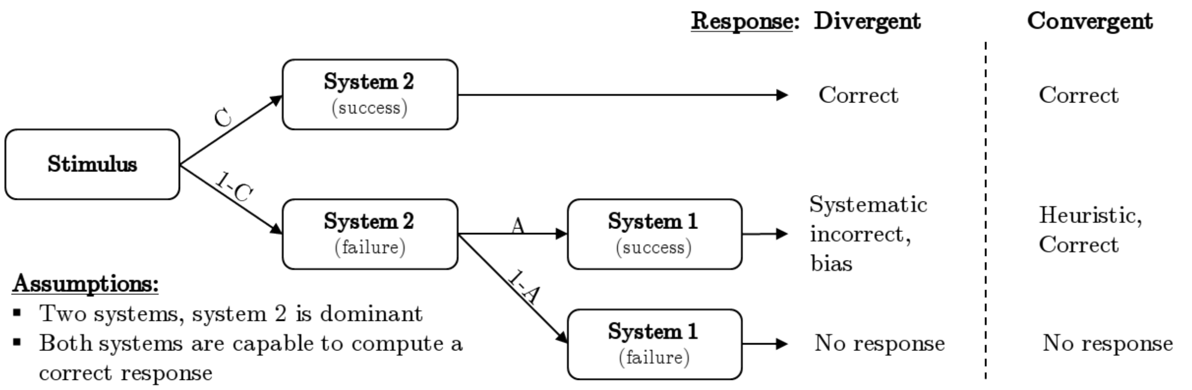

Figure 11: Process dissociation model of System 1 and System 2 processing with dominant System 2, based on Erdfelder et al. (2009); Conrey et al. (2005); Gawronski and Creighton (2013).

Process trees built on the assumption that the behavioural outcome of decision-making, measured by different frequencies of a nominal outcome variable (for instance *yes* and *no*) follow a multinomial distribution (Erdfelder et al., 2009). Following this rationale, different probabilities to a correct response can be calculated and the influence of the latent cognitive process can be estimated.

An established alternative tool to processing trees are generalized linear models (Erdfelder et al., 2009), with a dummy variable for the decision conflict. These models are also able to accommodate the specific characteristics of dual-processing theory, and provide a more general perspective on modelling and investigating cognitive processes. By modelling cognitive processes with a generalized linear model, different direct and indirect measures are regressed on the independent variable.

$$Response = Variable_i + Dummy_{Conflict} + Variable_i \times Dummy_{Conflict} \tag{2.2.1}$$

In the model the dependent variable is $response$ and as described by an independent variable termed $variable_i$, and a dummy variable $dummy_{Conflict}$, which represents the conflict of system 1 and system 2. This approach differentiates between the influence of the $variable_i$ regardless of the decision situation, or the response of the two systems. However, by considering the $dummy_{Conflict}$, the influence of the variable in case of process conflict (e.g. an intuitive reinforcement process and a deliberative Bayesian Updating process) can be measured (C: cognitive processing vs. A: automated processing). Consequently, $variable_i$ describes the influence of the variable itself, $dummy_{Conflict}$ the influence of the processing conflict, and $variable_i \times dummy_{Conflict}$ the influence of the intuitive processing on the decision outcome $response$.

Studies in dual-processing research rely on this approach to model competitive system 1 and system 2 processing. For instance, Alós-Ferrer et al. (2016) and Charness and Levin (2005) rely on it to model inertia in decision-making, and conflicting heuristic-intuitive and deliberative processing. (Achtziger & Alós-Ferrer, 2013) follow this approach to model decision-making under uncertainty.

Following this generalized linear model approach, the latent variable is measured by inducing process divergence and convergence by different tasks, and regressing on the decision outcome. Through investigation of the interaction effect of the variable and the divergence dummy the drivers of the latent cognitive process can be investigated. The discussed approaches rely on different measures of system 1 and system 2 processing. This is necessary, to validate the conceptualization and measure the conflict of the two systems.

In judgement and decision-making research, various other direct and indirect measures have been proposed to induce and investigate possible correlates of system 1 and system 2 processing. A first approach is to make usage of the relationship of System 1 and system 2. Following, Generalized Dual-Processing Theory, intuitive system 1 processing is effortless compared to deliberative system 2 processing (see section 2.1). As a result, system 1 processing is much faster than system 2 processing. Various studies have measured the active systems by comparing the response time in miliseconds (see e.g. Achtziger and Alós-Ferrer (2013)).

Another common approach is to work with bio-physiological correlates. Yerkes and Dodson (1908) have reported that deliberative decision-making works best with an intermediate level of arousal, while low arousal or high arousal reduces performance in complex cognitive tasks. This relationship is also known as the *Yerkes-Dodson-Law*, as illustrated in Figure 12.

Today, it is generally assumed that arousal significantly influences the proper functioning of system 2 (Kahneman, 2011; Strack & Deutsch, 2004). Dual-processing literature assumes (in analogy with the Yerkes-Dodson Law), that System 2, which is responsible for solving

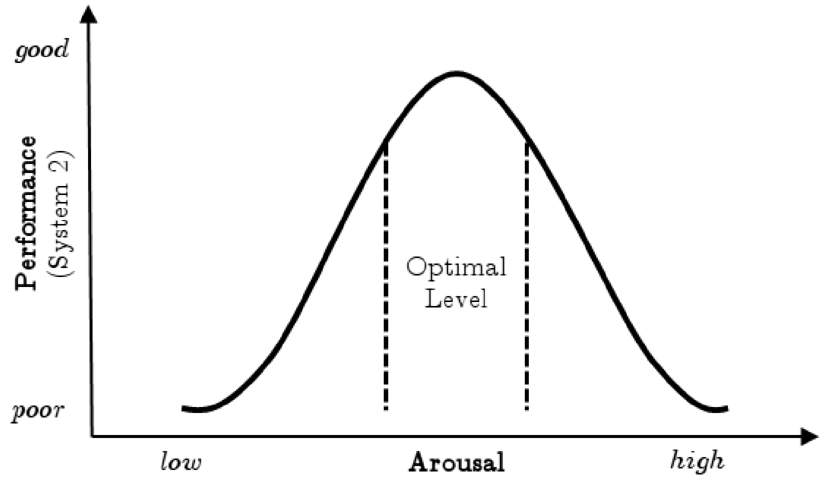

Figure 12: The performance of the controlled system 2 depends on an individual's arousal level, induced by the stimulus. Extreme arousal level are associated with poor processing, while intermediate arousal is associated with optimal System 2 processing, hence better performance in complex decision-making tasks.

complex tasks, works best for an intermediate level of arousal. High arousal is associated with low performance in experimental tasks requiring deliberative processing (Baron, 2000), while low arousal has been also explicitly linked to low performance of System 2 (Baumeister & Heatherton, 1996).

2.3 Using Choice Architecture to Overcome Biased Decision-Making

In the previous section, I focused on *the occurrence and theoretical explanation of cognitive biases and biased decision-making*, now I examine the application of the findings from Generalized-Dual Processing Theory. First, it should be mentioned that the original studies in the area of heuristics and biases literature investigated decision-making under uncertainty. For example, Daniel Kahneman received his Nobel Prize for his work on judgement under uncertainty. His numerous findings, which he published together with Amon Tversky (Kahneman & Tversky, 1972, 1973; Tversky & Kahneman, 1971, 1973, 1975) are based on the central assumption that people generally have difficulty making decisions based on probabilities and uncertainties. In particular, uncertainty can lead to a conflict between System 1 and System 2 (see Section 2.2). Under novel conditions, people tend to rely on heuristics, which can lead to systematic errors in probability judgements, what has been termed *biases* in judgement and decision-making research.

Numerous further studies have shown that these biases have been relatively robust and also have influenced by cognitive abilities (Stanovich & West, 2008). On the other hand, several papers on the topic of "Decision Support", have aimed to reduce the influence of biases (e.g. Arnott (2006)). Others have considered biased decision-making as an artefact of the decision-making environment, rather than the actual decision-making process. Other promising findings have been reported by Gerd Gigerenzer, who has focused on how information can be better processed and presented, thereby reducing biases (Gigerenzer & Hoffrage, 1995), possibility even eliminating them.

A further central step in the judgement and decision-making literature was taken over the numerous works of Richard Thaler and colleagues. Their work expanded the research in this field significantly by showing that errors or biases do not exist only under uncertainty, but also under certainty. They are also relatively robust and quite frequent across many decision-making scenarios. For instance, we know today that the endowment bias is independent of learning and experience (Thaler, 1999).

Building on this wide range of studies, Richard Thaler laid the foundation for the research stream of behavioural economics through a series of papers on market anomalies in human decision making, particularly in the *Journal of Economic Perspectives.* Thaler's work "Positive Theory of Consumer Choice" (Thaler, 1980) started other inter-disciplinary behavioural research streams. Across disciplines, behavioural research (e.g., behavioural economics, behavioural marketing and so on), has thus been concerned with better understanding human decision-making in domain-specific scenarios, and also with deriving recommendations for political actions, for example, or or interface design.

In this context, further works from Thaler followed the existing research in the field of heuristics and biases research. For instance, Thaler proposed an explanation of the endowment effect by means of the concept of loss aversion. In addition, Thaler proposed that if findings about biases (such as stability or ubiquity) are correct, these findings could be used to help people make better decisions. Thus, a central assumption of the behavioural economics literature stream is, that the systematic usage of these decision anomalies or biases can benefit humans. In particular, specific choice design interventions (so-called *nudges*) can help to reduce, and gain a better understanding of human errors in decision-making. This central credo of behavioural economics literature describes the concept of "libertarian paternalism", whose guiding principle is that private and public institutions should nudge decision-makers into the best decision for themselves, without eliminating people's freedoms (Thaler & Sunstein, 2003). As Thaler describes it more commonly, *"When we use the term libertarian to modify the word paternalism, we simply mean liberty-preserving. And when we say liberty-preserving, we really mean it. Libertarian paternalists want to make it easy for people to go their own way; they do not want to burden those who want to exercise their freedom"* (Thaler & Sunstein, 2008, p.6).

Building on insights of the biases and heuristics literature, Thaler and his colleague Sunstein created a theoretical framework termed *choice architecture*, which in turn is the consistent implementation of libertarian paternalism. Thaler describes the key concept of choice architecture with the following metaphor *"...designers need to keep in mind that the users of their objects are Humans [Comment: Thaler termed 'realistic' decision-maker, which are the opposite of the homo oeconomicus, as Humans, pp.5-6] who are confronted every day with myriad choices and cues. The goal of this section is to develop the same idea for choice architects. If you indirectly influence the choices other people make, you are a choice architect. And since the choices* *you are influencing are going to be made by Humans, you will want your architecture to reflect a good understanding of human behave. In particular, you will want to ensure that the Automatic System doesn't get all confused"*(Thaler & Sunstein, 2008, p.85).

Consequently, Choice Architecture postulates the systematic design of the choice environment to push decision-makers towards the best outcome of their own, without reducing their freedom. For that purpose, choice architects rely on a number of so-called *nudges*. Such interventions are "any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid" (Thaler & Sunstein, 2008, p.6).

Following this rationale, choice architects make use of a number of different design elements like default values or message framing to guide the decision-maker in the decision environment (Johnson et al., 2012). For instance, choice architecture has been successfully applied to increase the savings rates of employees (Thaler & Benartzi, 2004). The campaign team of Barack Obama set double-side printing as the default on all printers during the election campaign and is estimated to have saved about $ 40.000 (Thaler et al., 2014; R. Simon, 2008). In behavioural economics, many other policy-making scenarios are discussed that nudge people into options they would choose if relying on system 2 processing, and not cognitive short-cuts, heuristics or automated-intuitive decision-making (for an overview, see Thaler and Sunstein (2008)).

Choice Architecture also has relevant implications for decision support systems research. The studies of Mirsch et al. (2017); Weinmann et al. (2016); Jameson et al. (2014) expand the findings of Thaler and Sunstein, and provide a theoretical basis to make them usable in information systems research. For that purpose, they make use of so-called *digital nudges*. Digital nudges are nudges that coming in the shape of "interface (UI) design elements to affect the choices of users in digital environments" (Mirsch et al., 2017, p.634).

Since the concept is new in business informatics and information systems research, few studies make use of it (Hummel, Schacht, & Maedche, 2017). However, certain recent approaches fall back on digital nudges to intervene in the customer's journey in banking (Hummel et al., 2017), or to reduce technologicaly resistance, and increase the adoption of electro-mobility (Stryja, Satzger, & Dorner, 2017; Stryja, Dorner, & Riefle, 2017).

3 Part I: Designing Robo-Advisors

Abstract. *Robo-advisory or automated web-based investment advisory in particular promises many advantages for both banks and customers - but consumer adoption has been slow so far. Recent studies suggest that this lag in adoption might be due to a mix of low trust in banks, high expectations of transparency and general inability or unwillingness to engage with investment questions. Research in decision support and guidance shows customers' willingness to interact with a decision support tool depends greatly on its usability. I identify requirements for robo-advisory, derive design principles and evaluate them in two iterations with a real robo-advisor in a controlled laboratory study. The evaluation results confirm the validity of the identified design principles.*[1]

3.1 The Evolution of Robo-Advisory

In the context of service digitalization, human face-to-face banking encounters have been complemented by online (discount) brokerage and digital banking services (Sironi, 2016; Alt & Puschmann, 2016). In the 1970s, financial service providers targeted the U.S. middle class by introducing discount brokers. In the first step of the digitalization of wealth management, discount brokers provided financial intermediation services with significantly lower fees than the traditional advisors. The downside of this approach was the lack of personal financial advisory and the small range of available products. Because discount brokers buy and sell instruments at reduced commissions, the stock market became accessible to a new segment of customers.

With the rise of the world wide web in the 1990s, online trading and digital platforms became available to a much broader community. The service providers offered platforms ranging from networks for affluent investors, with retail investors managing their own portfolios to social trading platforms, where investors interact as in social networks and exchange trades and investment advice. This way, new customer segments have been developed. The current levels of digitalization in the context of financial advisory are digital service platforms like robo-advisors. According to Sironi (2016), the main goal of a robo-advisor is to support customers by translating their specific needs into an adequate portfolio of financial products and to subsequently manage the portfolio automatically. In particular, the advisory effort required to manage customers with a greater need for customized advice can thus be reduced.

Nowadays, bank account management and other banking services are offered fully digitalized. However, digitalized advisory services – especially if they are not provided by incumbent banks - still struggle for acceptance from retail customers despite their substantial cost-saving

[1]***Note***. *The content of this section is a revised version of two papers, which were created in the course of this thesis. In particular, the theoretical review of Section 3.2 builds on an article about robo-advisory for the Journal Business and Information Systems Engineering (Jung, Dorner, Glaser, & Morana, 2018), while the subsequent part of Section 3 builds on a three-cycle design sciences study in Electronic Markets - The International Journal on Networked Business (Jung, Dorner, Weinhardt, & Pusmaz, 2017). Other sources of this section are marked as such.*

benefits. Customers prefer hybrid solutions, allowing them to search for information and compare available products online, but still request human advisory before committing to an investment. Considering the bank and robo-advisor perspective, a combination of these services provides the opportunity to target the mass of less-wealthy customers, but also to generate additional revenue through separate fees (e.g. advisory in a branch is given for free, but robo-advisory phone support or additional features for security or access can be charged in relation to the effort required of the advisor). Furthermore, the robo-advisory business model is easily scalable, rendering the service an interesting business model from the service provider's perspective.

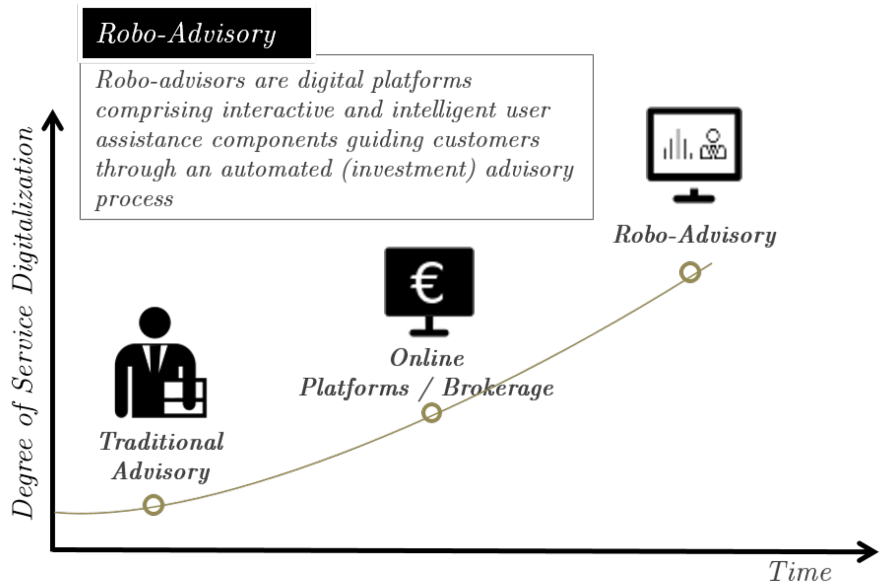

Figure 13: The digitalization of financial advisory services towards digital platform (based on Sironi, 2016).

3.2 Robo-Advisory and Financial Decision Support Systems

Recent robo-advisors are digital platforms comprising interactive and intelligent user assistance components (Maedche, Morana, Schacht, Werth, & Krumeich, 2016) that use information technology (IT) to guide customers through an automated (investment) advisory process (Phoon & Koh, 2017; Sironi, 2016; Ludden et al., 2015). In particular, robo-advisors differ from existing online investment platforms or online brokerage on two different conceptual levels: customer assessment, and customer portfolio management. The term *robo-advisor* is currently almost exclusively used in the context of financial investment advisory where robo-advisory increasingly replaces the classic retail customer advisory process. However, the generic concept of robo-advisory could be transferred to other domains such as health care or the real estate industry. In this work, I focus on financial robo-advisory in accordance with the prevailing meaning of the term.

Considering the customer assessment, robo-advisors extend existing advisory solutions, because they aim to transform the complete traditional, human-to-human advisory process into a digital, human-to-computer process. Traditional investor profiling conducted during in-person interviews and bilateral interaction is replaced by online questionnaires and self-reporting processes. The user's investment goals and purposes, risk affinity and aversion, and return and risk expectations are quantified by algorithms and automated processes on digital platforms. The assessment is not limited to risk profiling but can also include ethical and sector-specific preferences, for example, a preference for Islamic banking. Hence, human interaction in robo-advisory is limited to situations not directly related to the assessment or investment process, including IT-support or fraud management. Due to cost-savings by the automated customer profiling, and the management of the customer life-cycle, robo-advisors target the retail customer or non-professional segment, regardless of the user's actual wealth.

In addition, the customer portfolio management of robo-advisors differs from that of existing approaches. Customer portfolio management is defined as the management of portfolios including one or more financial products, in accordance with mandates given by clients, on a discretionary client-by-client basis (European Commission). Robo-advisory is predominantly based on products that require no or less active portfolio management like an "Exchange Traded Funds (ETF)". These funds replicate indices and hence require no active decision-making by portfolio managers regarding security selection and allocation. Cost structures are therefore often comparably simple and easier to communicate. The strategic asset allocation is based on the risk-profile of the customer and determined by a quantitative model. This combination of instrument and allocation selection can be fully automated and hence can considerably reduce management costs. The provisioning of the whole service via an online platform additionally reduces personnel and asset costs, while a higher number of customers can be served. The low complexity of these products makes them easier to explain to a wide range of customers along with other portfolio management-related advantages of ETFs.

With respect to customer portfolio management, robo-advisors can be further conceptualized into two distinct groups: active or passive regarding portfolio management, and dynamic or static regarding customer assessment. If the investment strategy and portfolio construction approach are fixed after the initial adjustment to a customer's profile, I classify the approach as static robo-advisory. The robo-advisor performs automated rebalancing only if the portfolio composition deviates from the optimum, for example, due to market developments. I further distinguish the rebalancing process. If the rebalancing is fully quantitative, I classify it as passive. If the investor only receives rebalancing suggestions and decides in self-directed ways the actual execution, I classify it as active.

In the case that the customer can adjust the overall strategy in a discretionary way at later points in time (e.g. change investment goals and volumes, reassess risk attitude), I classify the approach as dynamic robo-advisory. Furthermore, in contrast to previous digital services of online brokers or recommender systems, robo-advisors provide more sophisticated user interaction components (push notifications for market updates, opportunity and risk alerts, dashboards, periodic portfolio reviews) and automated execution, while optionally allowing for self-directed, discretionary intervention by the customer (development of a financial plan, integration of external accounts, or comparison of fees). In summary, the level of automation is comparably high. Figure 14 summarizes the previous conceptualization of robo-advisory.

Customer Assessment	**Retail customers as target segment:** ▪ The target segment is independent of actual wealth ▪ No customer screening or pre-selection process ▪ Public online platform, simple registration process
	Automated customer profiling: ▪ Self-reporting to quantify an individual's profile ▪ Questionnaires to measure the risk attitude ▪ Preferences, goals, special interests
Customer Portfolio Management	**Automated investment process:** ▪ The whole investment process of robo-advisors is automated and requires no human activity for profiling/portfolio management. ▪ Asset allocation is based on quantitative optimization ▪ Portfolio rebalancing: active (client interaction) / passive (quantitative only) ▪ Assessment: Dynamic (adjustments by customer) / static (fixed after initial process)
	Passive investment products: ▪ No actively managed financial products to reduce costs ▪ Instruments with transparent cost structure ▪ Common choice: ETFs, ETCs

Figure 14: Key characteristics of robo-advisory, organized in two clusters: assessment and management.

Robo-advisory platforms target customers, who cannot invest as much money as traditional wealth managers expect as a minimum investment (Ludden et al., 2015). Moreover, as market leader platforms residing in the U.S. demonstrate, robo-advisors attract the targeted customers with increasing success: For instance, the start-up Wealthfront accumulated 1 billion assets under management in less than 2.5 years after its market entry (Vincent, Laknidhi, Klein, & Gera, 2015). The volume managed by robo-advisors continous to grow, and it is currently estimated to have exceeded 20 billion in globally investable assets (Vincent et al., 2015). Optimistic forecasts predict that robo-advisors will manage 10 % of the whole wealth management industry by 2020 (Kocianski, 2016).

Given the contemporary digitalization of banking in combination with the interaction between provider and customer in the financial context, robo-advisors represent a promising research area that deserves more attention in the field of information systems. Robo-advisory is a young and nascent business model, and research focusing on understanding and designing robo-advisors remains scarce. Existing (design) knowledge on related systems within the IS domain could be adapted and extended for robo-advisors. For instance, the robo-advisor *Anlage-Finder* or *Max Blue* operated by Deutsche Bank failed on its first attempt due to legal problems and a sub-optimal user-experience (Dohms & Schreiber, 2017); it later relaunched as *Robin*. Hence, research on decision support, decision aids, product configurators, and recommender systems provide a valuable foundation that can support researchers and practitioners to better understand and design robo-advisors.

3.3 Problem and Solution Requirements

This section addresses the question of how to design robo-advisory solutions for unexperienced users. Prior research in information systems has indicated that transforming sensitive communication processes – such as financial advisory – from human to IT-based communication conflicts with human cognition and expectations and that the digitalization of human advisory is a difficult task (see Section 1). Recent research on consumer expectations of robo-advisory shows that – apart from quality of service – transparency, trust-building and the balancing of information asymmetries (Ruf et al., 2016; Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer, Matter, & Schwabe, 2012) are core issues in the design of digital robo-advisory solutions. Hence, the design of the user interface plays a crucial role in the speed with which such transformations are adopted and the level of resistance that users display towards them.

In this design science study, I examine the relationship between transparency, trust, information quality, information usability, and the consumer decision to invest (or not), from a design science perspective (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007; Vaishnavi & Kuechler, 2015). In an iterative procedure, I identify requirements and derive design principles, implement them in a web-based robo-advisory service and evaluate them in two mixed-method studies. The design principles guided my design process, and I will show that they increase the quality of the robo-advisor. My study is the first to focus on a user-centric perspective on robo-advisory design, with prior research mainly grounded in expert evaluations.

The main objective of this study is to design a robo-advisor that supports risk-averse consumers with little prior investment experience and relatively small savings to come to an investment decision. A robo-advisor is an "automated investment solution which engages individuals with digital tools featuring advanced customer experience, to guide them through a self-assessment process and shape their investment behaviour towards rudimentary goal-based decision-making, conveniently supported by portfolio rebalancing techniques using trading algorithms based on passive investments and diversification strategies" (Sironi, 2016). As a result, the advisory process of a robo-advisor is based on the traditional process of financial advisory.

Traditional human advisory services are structured in four (Cocca et al., 2016) to six major phases (Nueesch, Zerndt, Alt, & Ferretti, 2016; Nueesch, Puschmann, & Alt, 2014), and there exists no established advisory process for digital service systems like robo-advisory. Different aspects of digitalized financial advisory have been discussed in the literature (Kilic, Heinrich, & Schwabe, 2015; Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer, Matter, & Schwabe, 2012), which can be synthesized into the following three-phase approach. Based on Phoon and Koh (2017); Sironi (2016); Kilic et al. (2015); Nueesch et al. (2014); Nussbaumer, Matter, à Porta, and Schwabe (2012), I suggest to condensing the human advisory process to the following three phases of robo-advisory: configuration, matching and customization, and maintenance.

In the first phase, the configuration phase, the information asymmetry between customer and advisor is reduced (Kilic et al., 2015). This phase corresponds to the initiation, profiling, and concept and assessment phases of human advisory. In the next phase, the matching and customization phase, the gathered information is transformed into an investment recommendation. With the help of appropriate algorithms, customers receive recommendations that best fit their needs. The customers then decide to which of these offers they want to commit. If no recommendations meet their perceived needs, customers can reconfigure their profiles to receive alternative investment recommendations. Compared to other product configuration tools (like car configuration or clothing configuration), the characteristics of financial products can change unexpectedly (e.g. value or risk). Hence, during the maintenance phase, the difference between the actual needs and the recommendation has to be revised regularly, and reconfigurations of the product (rebalancing) need to be initiated in case of a substantial deviation due to economic developments or the changes of customer needs. Figure 15 depicts the process of a robo-advisor (Phoon & Koh, 2017; Sironi, 2016; Nueesch et al., 2014).

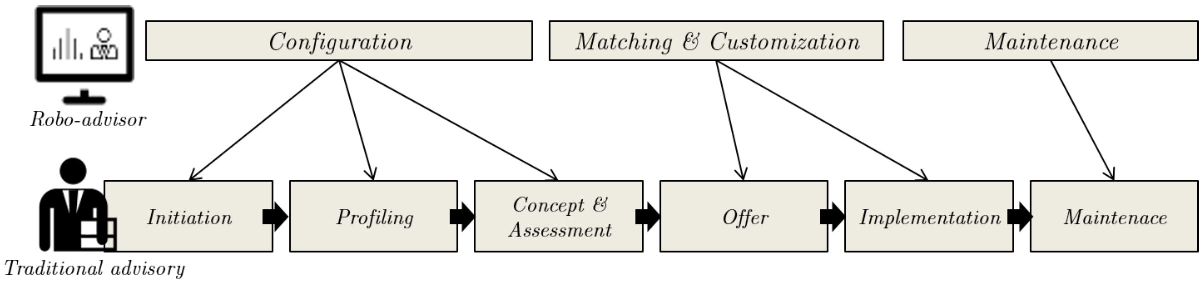

Figure 15: Iterative process of robo-advisory matched with a traditional wealth management process.

Based on this theoretical process model, I will now discuss and derive the main challenges of the digitalization of human advisory towards robo-advisory.

In the *product configuration phase* of a digital advisory service, the information asymmetry between customer and advisor is supposed to be reduced (Kilic et al., 2015; Nussbaumer, Matter, à Porta, & Schwabe, 2012). In a traditional advisory process, the advisor prepares the meeting with the customer (initiation), collects the customer's needs and wishes and identifies the customer targets during the meeting (profiling) (Phoon & Koh, 2017; Nueesch et al., 2014). Based on this information, the advisor develops a concept (Nueesch et al., 2014). In robo-advisory, these steps correspond to a product configuration process, where consumers translate their goals into a product specification by selecting and assessing options within a predefined product model (T. Hansen, Scheer, & Loos, 2003). Information asymmetries are reduced by the robo-advisor collecting data on the customer's financial situation and building a knowledge base of customer input (and behaviour, depending on which algorithms are deployed), and by the customer collecting and processing information about the robo-advisory process. Problems in this phase arise when information collection processes are too rigid and customers and advisors are “coerced into completeness” (Kilic et al., 2015). In this case, every single step of the information-collection process is discussed, which can lead to information overload and persisting information asymmetries (Kilic et al., 2015).

In the *matching phase*, the collected data is processed to yield a recommendation, and the recommendation is presented to the customer. The main goal is to transform customer input into a specific recommendation, explain to the customer how well their individual needs and wishes match the recommended portfolio, and describe the next steps of the advisory process (Nueesch et al., 2014). In robo-advisory, algorithms are employed to compute recommendations based on the input from the configuration phase. The customer then investigates these recommendations and can decide to invest in one or several of these recommendations. Problems in this phase arise when needs and recommendations are not well matched, which can lead to financial losses such as missed profit opportunities or, more severely, loss of invested capital. Mismatches occur for many reasons, for instance unexpected asset developments, lack of competence on part of the advisor, or deliberate steering of customers towards investing in products promoted by the advisor’s employer. The latter in particular has led to decreasing customer trust in bank advisors (Ruf et al., 2016) and probably poses an obstacle to robo-advisory usage when conflicts of interest arise (Securities & Commission, 2015) but are not made sufficiently transparent. Prior research has highlighted transparency in the robo-advisory process as one of the main concerns of (potential) customers (Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer & Matter, 2011).

In the *monitoring phase*, the advisor tracks asset performance and reacts to (expected) changes by rebalancing the portfolio. In robo-advisory, this task is essentially identical. Usually, trading algorithms automatically monitor and adjust investments according to consumers’ goals. Communication and transparency are key factors in this phase for building and retaining customer trust. These factors prose considerable challenge for the design of robo-advisors (Ruf et al., 2016).

Having this discussion in mind, I base my subsequent research on the design science method (Peffers et al., 2007). Design science is a research method to generate knowledge by an iterative evaluation of a design process of an IT artefact. It consists of the following phases: (i) problem identification, (ii) suggestion of key concepts to address these problems, (iii) development of a solution design, (iv) demonstration, (v) evaluation of the solution, and (vi) communication of central findings (Peffers et al., 2007).

3.4 Requirements Identification

My focus is the identification of design principles and requirements from the point of view of users with little investment experience and relatively small savings. For that purpose, I identify design principles used in my subsequent research. Design principles guide the design process by limiting the design space and helping to guide design decisions, reducing the complexity of the design process and helping to achieve a high level of design quality (Haki & Legner, 2013).

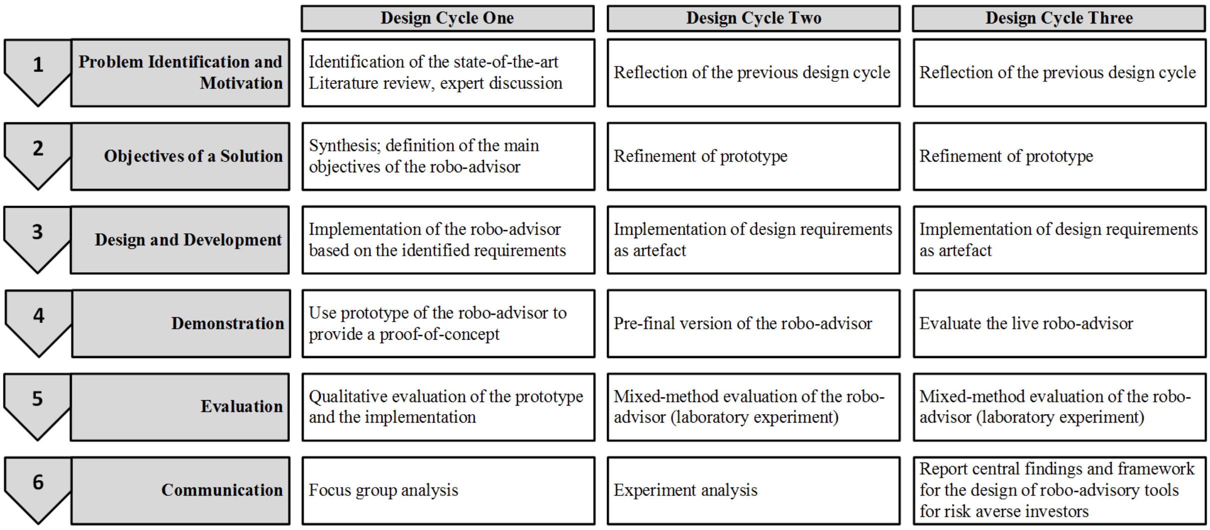

Figure 16: Design science research methodology based on Peffers et al. (2007).

To this end, I first carried out a literature review to determine the state-of-the-art of robo-advisor user-interface design (Webster & Watson, 2002). The meta search engine Google Scholar was used to search for sources containing the terms "robo advisor" in combination with "fintech", "investment", "transparency", "financial decision support" and "design", and "interface" or "usability" in the title, the abstract or the keywords. The search specified no range of years and yielded over 10,000 papers. By scanning titles and abstracts, I reduced this set to 61 potentially relevant studies. A backward search (Webster & Watson, 2002) yielded another 39 potentially relevant studies. Of these, only seven studies focused on the user-centric design of robo-advisory solutions. The other publications dealt with a range of other robo-advisory and FinTech-related topics, for instance the performance of different automatic asset allocation strategies (Musto, Semeraro, Lops, De Gemmis, & Lekkas, 2015), or how FinTech innovations affect traditional banks' competitiveness (Alt & Puschmann, 2016). All identified research focuses on expert-based evaluation. To the best of my knowledge, no prior research has taken the user-centric view when investigating requirements and design principles for automated solutions in advisory. I set out to fill this gap.

Table 8: Identified requirements for robo-advisory services based on a systematic literature review.

	Design Requirement	Key References
Ease of Interaction	**MR1.1 Ease of Navigation** How well control elements of the robo-advsior are integrated and how they are perceived by the user	Ruf et al. (2016); Ruf, Back, Bergmann, and Schlegel (2015); Nueesch et al. (2014); Korner and Zimmermann (2000); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)

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Table 8 – *Continued from previous page*

	MR1.2 Controllability Degree to which users have control over dialogues and behaviour of the robo-advisor	Ruf et al. (2016); Nueesch et al. (2014); Nussbaumer, Matter, à Porta, and Schwabe (2012); Korner and Zimmermann (2000); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
	MR1.3 Structural Consistency Consistent formal layout and content structure	Ruf et al. (2016); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
	MR1.4 Error Tolerance How well the robo-advisor deals with user- or system-induced errors	Ruf et al. (2016); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
Work Efficiency	**MR2.1 Effectiveness** How well the robo-advisor helps users to achieve their goals with a certain accuracy, completeness or reliability	Ruf et al. (2015); Möwes, Puschmann, and Alt (2011); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
	MR2.2 Efficiency Reasonable relationship between required effort to use the robo-advisory solution and the accuracy with which user goals are attained	Ruf et al. (2015); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
Information Processing and Cognitive Load	**MR3.1 Expectation Conformity** How well the user interface relates to the knowledge and experience of the user	Ruf et al. (2016, 2015); Nussbaumer, Matter, à Porta, and Schwabe (2012); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
	MR3.2 Ease of Understanding How much cognitive load is associated with understanding the retrieved information throughout the robo-advisory process	Ruf et al. (2016, 2015); "ISO 9241 Ergonomic requirements for office work with visual display terminals (VDTs)" (2018)
	MR3.3 Social Presence Degree to which the communicators behind the robo-advisor are perceived as being *present* or *real*	Ruf et al. (2016, 2015); Korner and Zimmermann (2000)
Transparency	**MR4.1 Cost Transparency** How easily cost or pricing models are found and understood	Nussbaumer, Matter, à Porta, and Schwabe (2012)

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Table 8 – *Continued from previous page*

	MR4.2 Process Transparency Level of following, comprehension of the possible activities and their succession in advisory	Ruf et al. (2016); Kilic et al. (2015); Nussbaumer, Matter, à Porta, and Schwabe (2012)
	MR4.3 Information Transparency Ability of the user to monitor and understand information, transparency about why certain data is needed from the user, and what happens to the data	Ruf et al. (2016); Nussbaumer, Matter, à Porta, and Schwabe (2012); Alt and Puschmann (2012); Möwes et al. (2011)

Second, I consulted literature and guidelines for interactive systems interface design for generic, standard design recommendations. In particular, I referred to the EN ISO norms 9241-110 and 9241-210 which summarize general design requirements for user interfaces, thus broadly defining relevant concepts and suggesting best practices. The basic principles for designing interactive systems, specifically human-computer dialogues, are suitability for the task, suitability for learning, suitability for individualisation, conformity with user expectations, self-descriptiveness, controllability, and error tolerance (EN ISO 9241-110). Based on my literature review, I derived twelve main meta-requirements and four design principles for the design of robo-advisors (Table 8).

Third, I circulated and discussed these requirements informally with robo-advisory and FinTech experts at our research institution, at banks, and at FinTech consultancies. Building on the findings of the expert discussions and the literature review, I consolidated our set of requirements into four design principles (Figure 17). Following Haki and Legner (2013), I carefully sifted out non-principles when consolidating my requirements (for instance, the experts mentioned goals pertaining to how a robo-advisor could increase revenues) to make sure that the principles I identify can indeed provide guidance for design decisions that "bridge strategy and design" (Haki & Legner, 2013, p.5).

- **DP1 Ease of interaction**
  General requirements concerning interaction with the artefact
- **DP2 Work efficiency**
  Support the users' ability to achieve their goals in an adequate time-effort relation
- **DP3 Information processing and cognitive load**
  Assist the user in information processing and understanding of the configuration
- **DP4 Advisory transparency**
  Provide cost, process, and information transparency

In the following, I briefly discuss each design principle and the meta-requirements from they are derived.

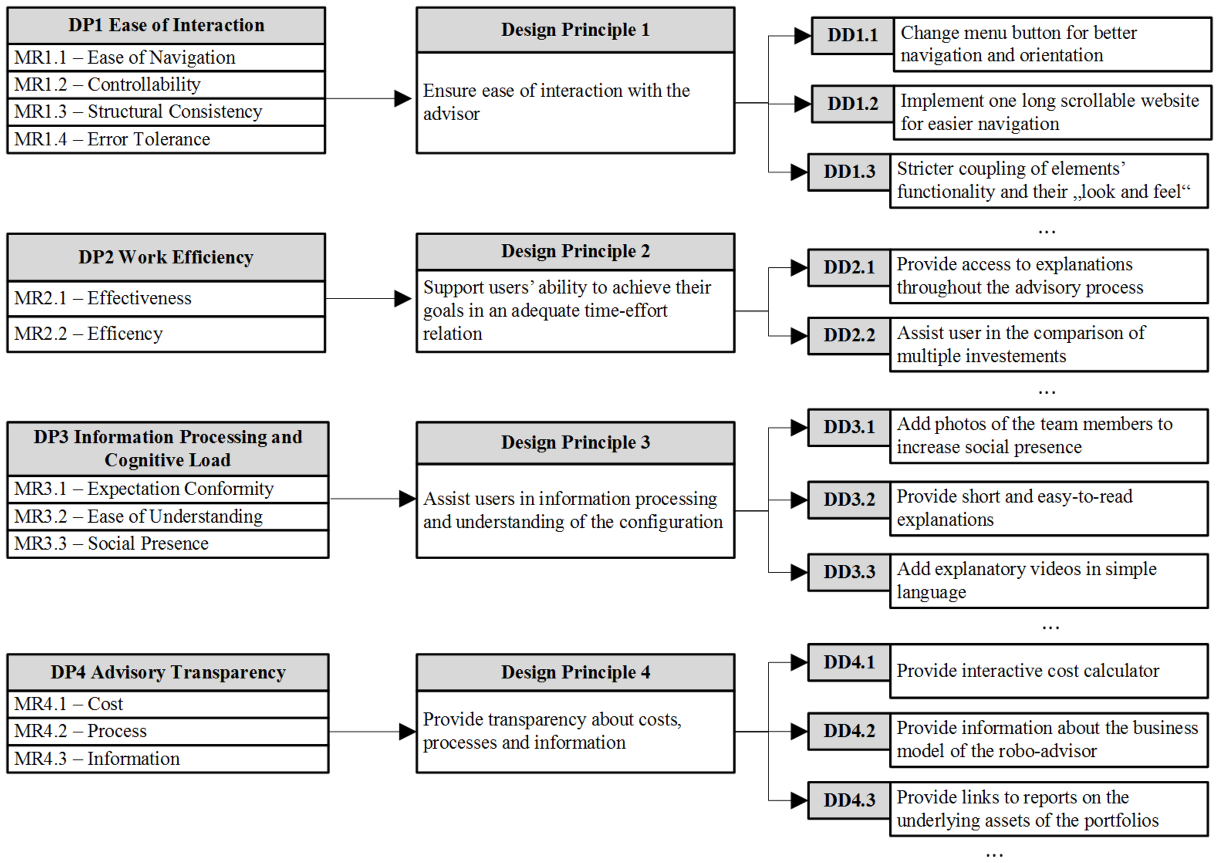

Figure 17: Meta-requirements, design principles and related design decisions.

3.4.1 Design Principle 1 (DP1) – Ease of Interaction

Information systems research has long identified (perceived) complexity as an important determinant of whether and how fast innovative information systems are adopted (Nueesch et al., 2014). Perceived complexity is determined, largely by ease of use, which has been cited as an important requirement for mobile financial advisory solutions (e.g., Ruf et al., 2015). Ease of use actually implies two further design requirements for a robo-advisory solution: ease of navigation, for example how well control elements of the robo-advisor are integrated and how easily they are found by the user (Nielsen, 1999), and controllability, for example the degree to which users have control over dialogues and behaviour of the robo-advisor (EN ISO 9241-110). A high degree of "ease of navigation" is evidenced, for example, in self-explanatory and easily located website menus (Nielsen, 1999). A high degree of controllability is obtained, for example, by giving users the opportunity to control direction and speed of processes according to their needs (going back, retrieving additional information etc.).

Structural consistency refers to the formal layout and the content structure of the navigation, interaction, and control elements. A high degree of consistency is derived in a uniform usage of colour coding or symbols for the same behaviours of the robo-advisor, and increases the self-descriptiveness of interaction options (EN ISO 9241-110). Error tolerance refers to how well the robo-advisor deals with user- or system-induced errors – for instance, hitting the “back” button during a payments process or inputting invalid data (EN ISO 9241-110).

Hence, I identify the requirements ease of navigation (MR1.1), controllability (MR1.2), structural consistency (MR1.3), and error tolerance (MR1.4).

3.4.2 Design Principle 2 (DP2) – Work Efficiency

Another important determinant of adoption and acceptance of innovative information systems is perceived advantageousness. Perceived advantageousness relates to how useful the IS is perceived in relation to other IT solutions (Nueesch et al., 2014). The usefulness of a robo-advisory solution can be understood in terms of how effectively and efficiently the robo-advisor supports the users in achieving their goals, i.e. finding and investing in an investment product that matches their needs and goals. This meta-requirement is grounded in the effort-accuracy framework (J. W. Payne, Bettman, & Johnson, 1993), which describes the relationship between user satisfaction, the effort required to achieve a goal and the quality of the achieved goal. User satisfaction increases, ceteris paribus, with reduced effort or increased quality. In this sense, I term the second group of requirements the "work efficiency dimension" and divide it into the two requirements effectiveness and efficiency.

Effectiveness describes users' ability to achieve their goals with a certain accuracy, completeness or reliability. In terms of robo-advisory, a highly effective robo-advisor provides all the information the user needs to make the investment decision in a comprehensible fashion. While high net-worth individuals value proactive information pushing (Ruf et al., 2015), this form of communication appears not to be a major concern for our target group. Their financial situation likely does not permit multiple (re-)investments, and the relative advantage of changing investments tends to shrink rapidly with the amount invested. Some research even suggests that regular investment updates may be counter-productive, nudging risk-averse consumers into making more frequent and less beneficial re-investment decisions due to fear of losses (Looney & Hardin, 2009).

Efficiency refers to the relationship between required effort to use the robo-advisory solution and the accuracy and completeness with which the associated goal of using it is attained. An efficient robo-advisor provides investment alternatives in an adequate time and reduces the configuration steps to a necessary minimum, helping customers to decide more quickly.

Hence, I identify the requirements effectiveness (MR2.1) and efficiency (MR2.2) as the work-efficiency requirements for a robo-advisor.

3.4.3 Design Principle 3 (DP3) – Information Processing and Cognitive Load

Another aspect in the design of robo-advisors is supporting consumers in the processing of information, and considering their cognitive limitations and their expectations towards communication and interaction modes (Ruf et al., 2016). Considering that the consumers in our target group are inexperienced, risk-averse consumers, they will need to absorb much new information, but lack the mental schemata for fast categorization and processing (Nielsen, 1999).

Hence, expectation conformity, ease of understanding and social presence play a large role in developing robo-advisors for this user group.

Expectation conformity means that the dialogue and the user interface relate to the knowledge and experience of the user, for instance from field of work, education, or generally accepted guidelines. If they do, the robo-advisor is less likely to be perceived as contradictory or confusing, and it will be easier for users to construct new mental models of the robo-advisory process.

Whether users will be confident in making their decisions depends greatly on whether or not the relevant information is easily available and understandable. While ease of interaction refers to the user's interaction with the robo-advisor (MR1.1-1.4) and efficiency refers to the degree of effort required to achieve the goal of enacting a suitable investment (MR.2.2), ease of understanding refers to how much cognitive load is associated with understanding the retrieved information throughout the robo-advisory process. High ease of understanding is associated with a relatively short time and few cognitive resources required to understand investment-related information and the robo-advisory process. That easy understanding does not imply leaving out information is stressed in DP4 (Transparency).

Social presence describes the degree to which the communicators behind the robo-advisor are perceived as "present" or "real" (Short, Williams, & Christie, 1976). Nussbaumer and colleagues suggest that this requirement is crucial for the success of robo-advisors since they lack by design human feedback and communication, which in turn is often perceived as lack of transparency on the part of the robo-advisor (Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer, Matter, & Schwabe, 2012).

Hence, I identify the requirements expectation conformity (MR3.1), ease of understanding (MR3.2) and social presence (MR3.3).

3.4.4 Design Principle 4 (DP4) – Advisory Transparency

In the context of IT-supported human advisory services, Nussbaumer et al. (2012) have found that customers are fixedly concerned with cost transparency, process transparency and information transparency. Highly transparent designs are associated with increases in customer satisfaction and willingness to pay. Cost transparency has two components: Customers must be able to easily find information on costs, and they need to understand eaily the cost structure. Costs of recommendation products like portfolio, influencing directly the effective return (Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer, Matter, & Schwabe, 2012). Process transparency relates to how easy one can follow and understand activities and their succession in the advisory process (Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer, Matter, & Schwabe, 2012). Information transparency, finally, refers to providing the customer with clarity on why certain information is needed during the advisory process, and the "degree of the client being enabled to monitor and comprehend the information used as the basis of decision-making and to assess their [decision's] quality and suitability" (Nussbaumer et al., 2012, p.4). Kilic and colleagues (2015) have examined how process rigidity during the first phase of advisory, namely information collection, affects the relationship between customer and advisor. Since the goal of this phase is reducing information asymmetries, a phenomenon called "coercing into completeness" may occur (Kilic et al. 2015). This describes interactions between customer and advisor where every single bit of information, regardless of its relative importance for the particular customer, is discussed "for the sake of completeness". Process rigidity can exacerbate this phenomenon, which is generally linked to negative outcomes regarding understanding and transparency, thus perpetuating information asymmetries. A number of studies deal with the question of how to establish an appropriate level of detail in customer-advisor interactions to ensure all relevant information is provided but the customer is not overwhelmed (Kilic et al., 2015; Nussbaumer, Matter, à Porta, & Schwabe, 2012; Nussbaumer, Matter, & Schwabe, 2012).

Hence, I identify the requirements cost transparency (MR4.1), process transparency (MR4.2), and information transparency and privacy (MR4.3).

Next, I conducted benchmark research identifiying current robo-advisory platforms that cater to inexperienced, risk-averse, and less wealthy consumers (Asset Builder, Betterment, Cashboard, Easyfolio, Future Advisor, Hedgeable, Jemstep, Learnvest, Personal Capital, Moneyfarm, Schwab Intelligent, SigFig, Trizic, Upside Advisor, Vaamo, Vanguard Personal, Wealthfront, Wise Banyan). Since these consumers generally do not wish to (or are not able to) invest large sums and are likely price-sensitive, I focused on robo-advisors that do not require an account minimum and do not charge set-up fees. I carefully analysed these robo-advisors in order to check the applicability of our requirements and design principles and to check our list for completeness.

3.5 Design, Development and Demonstration

This section describes the iterative consumer-centric approach I followed for designing and developing a robo-advisory solution that would adhere to the identified requirements. One common approach in usability engineering is the scenario-based approach (Rosson & Carroll, 2002). This approach places the user and the user's needs at the center of all design and development activities. As recommended by Peffers et al. (2007), I iterated different design cycles to design and develop the robo-advisor. The robo-advisory design requirements were implemented and evaluated in collaboration with a partner company that had just begun development of their robo-advisory solution, explicitly targeting inexperienced, risk-averse and non-high-net-worth users. In the first design cycle, I implemented a prototype of the robo-advisor to provide a proof-of-concept. In the second design cycle, I developed a pre-final version of the robo-advisor and in the third design cycle, I evaluated the live robo-advisor. In order to reduce development complexity, I decomposed the process into sub-problems (MR1 to MR4) as proposed by Peffers et al. (2007).

Design Cycle One: The main goal of the first design cycle was a first evaluation of the artefact prototype. Furthermore, I conducted a series of expert interviews with employees at the case company to gather relevant problems and challenges. The research team examined the robo-advisory solution independently to assess how well it fulfilled the requirements. The research and development teams were staffed separately which helped solicit a broader opinion base unfettered by “doability” concerns. The identified design principles were evaluated in a qualitative focus group with employees of the case company.

Design Cycle Two: The goal of the second design cycle was to provide a systematic evaluation of the design in a laboratory setting. In particular, I evaluated the two phases product configuration and matching. Robo-advisory design was evaluated in a mixed-method experimental usability study. The study investigated the adoption of the robo-advisor by subjects belonging to the target customer group. The findings of the first study were analysed and discussed with leading employees of the case company.

Design Cycle Three: The third design cycle served to refine my design principles and to evaluate the design decisions I made based on the results from the second cycle. After being adjusted to suit the previous findings, the design requirements were executed in a fully functional system. The artefact was evaluated in a mixed-method experimental usability study. In cooperation with the case company, the requirements were discussed and a design framework was derived (see Section 3.7).

3.6 Evaluation

I adopted a mixed-method approach to evaluate the robo-advisory solution following the design science method in cycle 2 and cycle 3 (Peffers et al., 2007). In both studies, I used screen recording, the think-aloud method, and standardised and non-standardised questionnaires to investigate user behaviour. In the second study, I combined these measures with the scenario technique, click-stream analysis and a standardized risk test (Holt & Laury, 2005).

Think-aloud protocol: The think aloud protocol is a popular method for user-centric usability studies (Jaspers, Steen, Van Den Bos, & Geenen, 2004) and has been applied successfully in the development of information systems. This method aims to determine how users experience a system, especially when solving a problem or performing a task within it. The user is asked to use the system while verbalizing everything that goes through their minds. The think-aloud protocol is well suited to detect usability problems such as cognitive overload or inappropriate representations. I prepared interview guidelines to make sure that all requirements would be commented upon. The interviewer was briefed to remind users to verbalize their thoughts in case they remained quiet for more than 30 seconds and, in case the user did not comment upon a requirement, to elicit the user’s opinion on it. I recorded the interviews and transcribed them for analysis.

Screen recording: The previously illustrated think-aloud method is often combined with screen recording or screen casting, which helps one to interpret and understand the user intentions better than based on audio recording alone. In both studies, I recorded user behaviour with Camtasia studio and used the audio and video file to transcribe the user comments from the think aloud-method (Nielsen, 1999).

Questionnaires: In both studies, I used questionnaires to collect demographic characteristics. I also surveyed the participants' level of financial knowledge and opinions of financial products in general and of robo-advisory in particular.

Click-stream analysis: This method describes the recording of the clicking behaviour of users while browsing or using specific software applications. It is a method established for tracking and studying consumers' decision-making processes (Senecal, Kalczynski, & Nantel, 2005) and in usability design (Ting, Kimble, & Kudenko, 2005). I used the log files to track user interactions with the robo-advisor and in order to check whether perceived behaviour corresponded with real behaviour (e.g. perceived vs. real amount of scrolling through information pages).

Risk test: Researchers in economics and psychology have developed different questionnaire and scales to measure and describe the risk attitudes of decision makers. Some of the most commonly used methods are multiple price lists or lotteries (Charness, Gneezy, & Imas, 2013), where decision makers are asked to select from paired gambles with different risks. By computing the utility of each gamble, risk attitudes can be estimated. I used the multiple price list as proposed by Holt and Laury (2005). This list allowed us to separate risk-averse user from risk-neutral users, and to compare these groups in my evaluation.

Friendly user and scenario: Scenario techniques are a popular method to encourage the user to behave more naturally, and to help them begin a task. In the third design cycle (second experimental study) I asked users to inform themselves about a private investment with a specific goal (e.g., holiday, car). Users were then asked to form an opinion on whether the robo-advisor would be helpful to achieve this goal (Rosson & Carroll, 2002).

Participants and setting: The pretests for both studies were performed in Karlsruhe Decision and Design Lab (KD2Lab). Participants were aged between 18 and 26 (n=30, male=16) and recruited using a standard recruitment tool for laboratory experiments, ORSEE (Greiner et al., 2004). In the first study (n=11, male=7), participants received 12 Euros each as incentive to participate. In the second study (n=19, male=9), they participated in exchange for a participation payment of 8 Euros and a performance-based payment (risk questionnaire) between 0.10 and 3.85 Euros. In the first study, I elicited participants' risk aversion informally. In the second study, I used the Holt and Laury's (2005) risk test. Nearly all participants (13) were risk-averse. Three participants were risk-neutral and three tests were filled in incorrectly.

3.7 Findings and Communication

Prior to starting the product configuration process, participants interacted with the website in order to find more information on the robo-advisory provider, on prices, on general product information (e.g. how an investment fund works) and on terms of service. The evaluation of design principle 1 (Ease of interaction) and its related requirements showed, in both studies, that participants paid close attention to it and that they used it as an informational cue for robo-advisory trustworthiness. Several participants in the first study made similar remarks to the effect that failure to find the menu button and to orient themselve on the homepage (MR1.1 Ease of navigation) made them question the integrity of the robo-advsior: "The website is a mess – I wonder whether they work as sloppily as they design their website". The menu display was changed for the second study (DD1.1) at which point it no longer attracted complaints. The design decision DD1.2 of implementing one long scrollable website for easier navigation and controllability (MR1.2) and easier switching between handheld mobile devices and stationary computers received mixed remarks in the first study. This was mainly due to confusing links: "When I click on a link, I jump somewhere on the website and don't understand where I am or how to get back...". This problem is popularly termed the lost in hyperspace problem (Hardman & Edwards, 1989). Nearly all participants reported this issue, which was associated with increased reluctance to trust the robo-advisors recommendations and dissatisfaction with both the configuration process and the product. Changes on the website to reduce "jumping" led to a much more positive evaluation in the second study, where the website concept was lauded as modern and up-to-date. Structural inconsistencies (MR1.3) make it difficult and confusing for users to interact with the robo-adivsor. Several participants voiced discontent regarding the implementation of this requirement: "I am not sure if the pictures are supposed to link to somewhere. Some keywords look like links or interaction elements for me...". This issue was partially solved between the first and the second study through a closer link between elements' functionality and their "look and feel" (DD1.3), leading to a decrease in critical comments. Error tolerance (MR1.4) was an issue in the first evaluation study, where hitting the browser's "back" button would result in expired empty screens. Violations of design principle 1 (ease of interaction) were often commented on with reference to design principle 3 (assist in easy cognitive processing of information related to investment decision and advisory process): "All this scrolling past so much information is exhausting. I have to spend so much effort on understanding the website that I don't feel like spending effort on understanding the products...".

Issues pertaining to design principle 2 (work efficiency) were raised by many participants of the first study. Specifically, they felt that the configuration step was confusing. Some considered the functionality of the configuration interface to be counter-intuitive (violation of MR3.1 expectation conformity) which reduced their trust in the fit of the proposed investment to their goals (MR2.1 effectiveness). The layout of the configuration interface was changed between the first and second study to align the "look and feel" of the website with its expected functionality, which resulted in much more positive user comments. Some were looking for easy access to additional information during, not before, the configuration process: "Oh, I wish I could go back to the page that explains what an ETF is". The robo-advisor was changed accordingly (DD2.1) and this issue was not raised again in the second study. On a more general level, this observation fits with a range of other comments by participants on whether the robo-advisor provided enough information for them to feel they could make a goal-directed decision: "Well, I would probably consult an external comparison website before making a decision – the robo-advisor gives a lot of information, but I value an independent opinion". Interestingly, many said they would rely on the opinion of their parents. With regard to efficiency (MR 2.2 efficiency), participants asked for better support in comparing different investment alternatives – "I cannot compare more than two alternatives with the current graphic design". For the second study, I implemented an interactive design element to support direct comparisons between investment alternatives (DD2.2). This design shiftsubstantially reduced the number of negative comments on this issue in the second study. Violations of design principle 2 were commented on with reference to design principle 3: "For the comparison, I actually have to remember the names of the alternatives I want to compare. That is exhausting". Overall, design principle 2 was evaluated much more positively in the second study.

Design principle 3 (Information processing and cognitive load) received mixed comments in the first study and predominantly positive comments in the second. This improvement was due to changes to the robo-advisor regarding two underlying requirements. Expectation conformity was improved upon by a more intuitive design for the configuration interface. Social presence was improved upon by giving more details about the employees of the company, including pictures and links to social business network profiles (DD3.1): "Wow, these are actual people! That makes the robo-advisor much more trustworthy, in my opinion". Clickstream analysis showed that they spent quite a long time perusing social information. Several participants, especially females, mentioned that they would definitely want to contact the company by telephone before making an investment, not necessarily because they had questions that were not answered on the website, but just because "I would feel better about the investment after talking to a real person". Ease of understanding was commented upon positively in both studies: "They do a really good job explaining difficult finance concepts, with examples and in short sentences, and in a very friendly fashion". Participants voiced criticism regarding the amount of text: "There is so much text! Can't they use more visual explanations?". In the second design cycle, textual explanations were shortened and made less technical (DD3.2), and explanatory videos were added to the robo-advisor (DD3.3) and rated very favourably by most participants, both with respect to social presence and ease of understanding. One participant noted that he considered the videos too playful for a serious matter such as investment decisions. Clickstream analysis showed that, on average, participants paid much attention to the videos.

The evaluation of design principle 4 (Advisory transparency) showed marked improvement from the first to the second design cycle. Participants commented positively on the interactive cost calculator (DD4.1) and, as clickstream analysis showed, spent much time familiarizing themselves with the cost structure. Process transparency was overwhelmingly rated good, but one participant noted that he felt lost during configuration: "I could not understand the logic [of the advisory process] and did not know what to expect next". Providing more easily understandable information on the process improved perceptions in the second study. In addition, the business model of the robo-advisor was explained in greater detail (DD4.2) in order to enhance both cost and process transparency. Information transparency was rated as good, for one because it was easy to understand, for another because most participants found the necessary information fast, except for comparisons to other robo-advisors. One issue in the first study was missing information on the portfolios' underlying assets, which was added prior to the second study (DD4.3). One participant noted, "I have the feeling that some information is missing, but could not explain exactly which information". Participants in the second study reported, on average, better understanding of and higher satisfaction with the products. Several participants explicitly noted that the interactive comparison element for portfolios, and the resulting increase in information transparency, weighed positively in their considerations of whether to invest with this robo-advisor.

Overall, about half the participants in the second study (n=9) indicated that they would be willing to invest money with the robo-advisor and that they felt the website left an impression of trustworthiness. This impression signals a marked improvement over the first study, where the majority of participants did not consider the robo-advisor trustworthy and would not have considered investing money with it. The most frequent answers given in the second study were similar to the following participant's: "I would start off with a small amount, see how it goes and if it performs well and I feel comfortable with it, I'll consider investing more". Several participants did stress, however, that they would definitely want to speak to a human advisor before investing with the robo-advisor, either through the robo-advisor's hotline or at their current bank. Interestingly, when asked why, most participants were not primarily concerned with obtaining specific additional information (e.g., comparisons with other advisors or products) but rather with talking to a real person. "If they could convince me in a personal meeting that they are trustworthy, I would definitely invest". The remainder of the participants were split between "undecided" and "opposed" towards an investment. Undecided participants mostly noted that they would take more time to compare with other robo-advisors and bank products. The reluctant participants, frequently explained that they would invest only with a human advisor or do their own research on investment, and that they did not feel they wanted to risk even a small portion of their monthly income.

Overall, participants reported that the impression of trustworthiness was one of the major factors in their attitudes towards robo-advisors. If participants said they would not invest, they invariably reported missing trust-building aspects like press reports, testimonials, or personal contact. Transparency and usability played a large role in shaping the impression of trustworthiness. Nearly all participants who expressed an unfavourable opinion of the robo-advisor explicitly referred to usability issues when asked to explain their opinion, for instance expressing the lost in hyperspace problem (Hardman & Edwards, 1989), as occurred in the first study.

None of the participants felt informed well enough to form an opinion of how good the products were, but very few indicated that they would be willing to educate themselves more thoroughly on private investment. In line with this trend, I found that simplifying and shortening explanations of financial concepts between the first and second design cycle increased, on average, both willingness to invest on this website and average reported satisfaction with the robo-advisor. Female participants in particular commented very favourably. The most frequently reported reason not to invest (straight away) was transparency-related: nearly all participants stated they would first solicit an independent opinion of the robo-advisor's quality and refer to robo-advisory price comparison reports and websites. The interactive product comparison elicited positive comments and was cited as a reason to invest with this robo-advisor.

For further communication, I summarize my results in the **house of robo-advisory design**, which presents the four design principles of robo-advisory design that shape customer intention to adopt a robo-advisor (Figure 18).

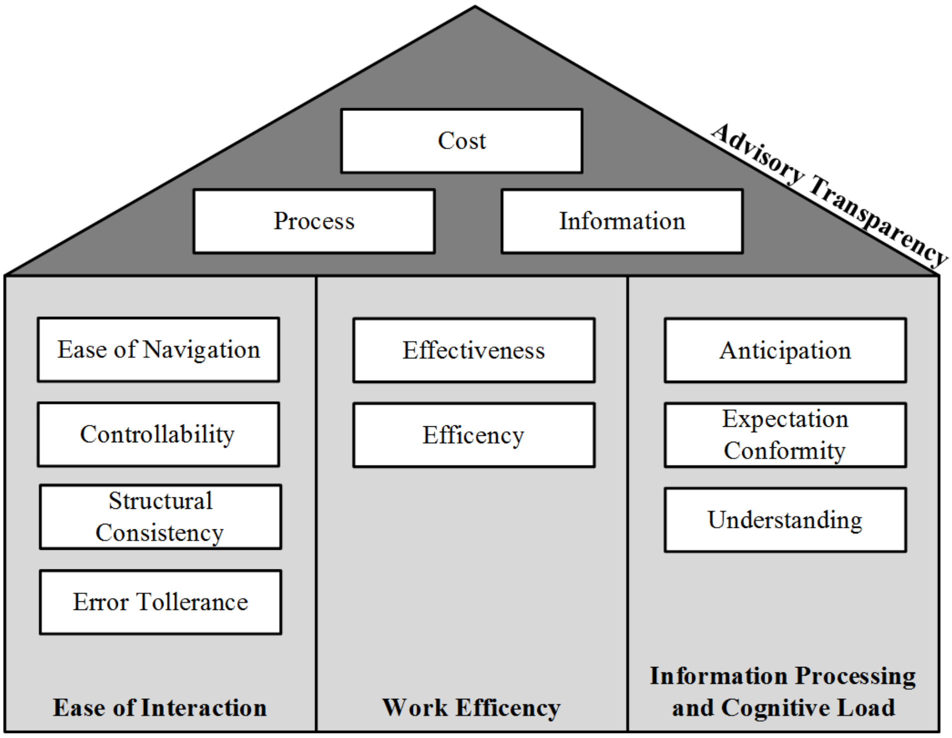

Figure 18: House of robo-advisory design, with ease of interaction, work efficiency and information processing dimensions as cornerstones of advisory transparency.

3.8 Discussion

My research addresses the question of how to design robo-advisory solutions for risk-averse, low-budget, inexperienced consumers. Prior research has indicated that the accessibility and comprehensibility of the user interface plays a large role in how fast and how reluctantly IT innovations are adopted (see Section 1).

To the best of my knowledge, this is the first study investigating the design and transformation of digital advisory into robo-advisory from a user-centric perspective. Prior research has focused on specific aspects of the design of IT-supported advisory, such as transparency (Kilic et al., 2015) or service encounters (Nussbaumer, Matter, à Porta, & Schwabe, 2012). I contribute to robo-advisory literature by identifying, implementing and evaluating four core design principles and their underlying requirements. Following a design science research process, I identify and evaluate a broad set of design principles for building a robo-advisor interface for inexperienced, risk-averse and less affluent users. My study is exploratory in nature, and provides a better understanding of the users' view on the digitalization of advisory services and it contributes towards improving the theoretical foundations of the design of robo-advisory services.

My study is, to the best of my knowledge, the first to identify and evaluate design principles for robo-advisory in an iterative fashion with both experts (in the first design cycle) and potential users (in the second and third design cycles). The evaluations of the artefacts generated during each design cycle show that guiding robo-advisor design with design principles, and subsequent design decisions, improved usability and transparency, and furthermore users' trust in and satisfaction with the robo-advisor improved. Social presence played a surprisingly large role, with the majority of participants across both studies stating that they would want to speak to a human advisor prior to making an investment with the robo-advisor. This tendency was most pronounced from female participants, who commented particularly positively on the design decisions made to increase social presence. Male participants tended to react more strongly to perceived lapses in ease of interaction; the design decisions made to improve ease of interaction led to much more positive evaluations in the second study. Both genders reacted positively to the design decisions taken to improve advisor transparency and make information processing easier; only a small minority of male participants would have preferred more "technical" and complicated explanations. All participants used the degree of usability as a cue for trustworthiness, with inter-individual variations on how much emphasis they placed on each dimension. Our results support prior research in that transparency was widely reported as the most important driver for customer trust in the product and the robo-advisor in general.

Overall, my research suggests that the current design of robo-advisory solutions does not (yet) sufficiently meet the needs and wants of risk-averse, low-budget, inexperienced consumers to make them trust the robo-advisor and invest readily. My studies show that design issues are explicitly used as cues for inferring the trustworthiness of the robo-advisor and its quality of service. This finding supports our belief that our research on robo-advisory design provides vital insights for developing solutions suitable for this consumer group. Specifically, current robo-advisors for this consumer group ought to be evaluated with regard to our proposed design principles. My evaluation study shows that many important design decisions pertain to interface elements that are relatively easy to change and that one design decision may affect several design principles, directly or indirectly (e.g., improving ease of understanding positively affects perceived advisor transparency). For practical applications of my research, the design principles and the underlying meta-requirements can be used to analyse robo-advisor interfaces and to evaluate the improvements expected in implementing our proposed design decisions.

In addition, my study suggests that the threshold for first-time online investment might be too high for this kind of consumer to overcome alone; banks considering moving customers from human advisors to robo-advisors may want to consider developing (human) advisory plans to gradually shift customers from one service to the other - for instance, integrating the robo-advisory solution in human advisory processes. Otherwise, these customers are likely to prefer the status quo, either investing nothing or relying on human advisory. Considering that banks are continually downsizing advisory operations except for high net-worth individuals, robo-advisory services are likely to become the only way for average and below-average income earners to participate in financial investment.

4 Part II: Conceptualizing Decision Inertia

Abstract. *Decision-makers tend to repeat previous choices regardless of outcome (a phenomenon called decision inertia). In this section I review the most relevant studies concerning decision inertia research in judgement and decision-making, neuroscience, and information systems. Based on the literature review, I discuss the identified measures of decision inertia, the different experimental tasks used to measure it, and their characteristics. Consequently, I propose an experimental framework for measuring and investigating decision inertia in the lab, and I derive research hypotheses to explain decision inertia. Relying on that theoretical groundwork and the research hypotheses, I present three related experimental studies to investigate the drivers of decision inertia. The results show that decision inertia is driven by motivational and cognitive factors, and is a multi-determined bias. The findings of this Part II provide a theoretical foundation to design counter methods to overcome decision inertia, which is the purpose of Part III of this thesis.*[2]

4.1 Decision Inertia in Decision-Making

Decision inertia has received much attention in recent research, due to its implications for economic decision-making (Alós-Ferrer et al., 2016; Erev & Haruvy, 2013). Decision inertia is the tendency to repeat a previous choice, regardless of the obtained outcomes (Sautua, 2017; Alós-Ferrer et al., 2016; Dutt & Gonzalez, 2012). It can be driven by other cognitive or motivational processes like consistency-seeking (Alós-Ferrer et al., 2016), decision avoidance (Sautua, 2017), or costs of decision-making (Bawa, 1990), and it manifests as a kind of status quo bias or resistance to revise a decision (Dutt & Gonzalez, 2012).

The concept of decision inertia has been used to explain irrational reliance on previous choices in numerous settings. For instance, it has been investigated as a potential explanation of consumers' reluctance to patronize new brands and their attachments and persistence with incumbent products (Li, Liu, & Liu, 2016; Polites & Karahanna, 2012), inertia in investment decisions (Sandri, Schade, Musshoff, & Odening, 2010) and economic decision-making under risk (Alós-Ferrer et al., 2016; Charness & Levin, 2005). Bar-Hillel and Neter (1996) illustrate decision inertia also in probability reasoning: People tend to keep their lottery ticket over other available, clearly superior investment options. Decision inertia also has serious implications for computational judgement and decision-making research (Erev & Haruvy, 2013), for instance Dutt and Gonzalez (2012) use inertia in computational modelling of human decision-making, and Akaishi, Umeda, Nagase, and Sakai (2014) consider decision inertia in explaining and modelling choice repetition in neuro science studies, observing a tendency to rely on previous decisions but regarded it as noise.

As I describe in the next section, numerous experiments have established that inertia in decision-

[2] ***Note***. *The content of this section is a revised version of two papers, which were created in the course of this thesis. In particular, Section 4.2.2 is a revised version of Jung and Dorner (2017), while Section 4.3, 4.4, and 4.6 is adopted from Jung, Erdfelder, Broeder, and Dorner (in press), and Section 4.3 and 4.5 from Jung, Staebler, and Weinhardt (2018). Other sources of this section are marked as such.*

making is a dynamic process with multiple determinants, and it underlies a systematic deviations from rational behaviour (Jung & Dorner, 2017). Based on this kind of perspective, Alos-Ferrer and colleagues propose a multiprocess scheme of inertia in decision-making, on which I rely in this work. The authors suggest that decision inertia, or "the tendency to repeat a previous choice, regardless of its outcome, in a subsequent decision" (Alós-Ferrer et al., 2016, p.1) is an automatized, unconscious, and effortless process, that conflicts with rational, slow, resource-consuming deliberations like correct Bayesian updating (Alós-Ferrer & Strack, 2014). This conceptualization of decision inertia, suggests that the manifestation of decision inertia is believed to be present when decision inertia and intuitive and deliberative decision processes conflict. Because conflict resolution is effortful, it diminishes decision speed (Alós-Ferrer et al., 2016; Brody, 1965) and increases suboptimal decisions and error rates (Alós-Ferrer et al., 2016; Alos-Ferrer, Garagnani, & Hügelschäfer, 2016). Decision inertia manifests in suboptimal outcomes, because individuals cannot, or do not consider the full consequences of their decisions, and relying instead on automatic and impulsive decision strategies.

Previous research provides evidence for this rationale, for instance Marcos et al. (2013) has observed an inability of individuals to decide without relying on their past decisions. Decision makers always let previous choices influence recent decisions, regardless of the instruction to make these decisions independently. This influence of previous choices in consecutive decision tasks, has been observed in numerous studies (Fecteau & Munoz, 2003; Gold, Law, Connolly, & Bennur, 2008; Akaishi et al., 2014). Recent research shows that the phenomenon underlies a systematic, autonomous mechanism (Akaishi et al., 2014). In a Functional Magnetic Resonance Imaging (fMRI) study, where decision makers had to guess the direction of the motion of random dots, participants tend to repeat the choices they made in previous trails. Akaishi et al. modelled this behaviour with a learning rule indicating a system in the valuation and information processing behind this phenomenon.

In the next steps, I take up these findings, and review recent decision inertia research. Because the aim of this work is to transfer these findings to economic scenarios and considerations of decision support systems, I focus on decision inertia

- under risk,
- based on experience,
- in subsequent decisions, and
- in economic or related decision scenarios

The first limitation is, that I focus on decision tasks *under risk*. Decisions are made under uncertainty, where each decision can be a win or a loss. This assumption is intended to ensure the transferability of findings to the financial context, as financial decisions are predominantly risk-prone, since even "safe" financial products involve a certain risk of default.

Furthermore, I investigate decisions based on experience, meaning that decision-maker make decision by themselves and show decision inertia by themselves. They are not faced with a row of previous decisions and they do not have to make decisions based on decisions they did not make alone. This specification is important to mention, because some studies (e.g., inaction inertia studies), face decision-makers with decision scenarios that presuppose the decision maker behaved in a specific manner before. As a result, decision-makers must face consequences they did not "cause in reality" (e.g., "You missed offer A in this shop last week, will you still buy there this week?".

Related to this issue is my focus on subsequent decisions, I consider only dual-choice scenarios. In these tasks, the decision-makers make a first and a second decision. Then the second decision is investigated and analysed. This kind of dual-choice task is considered repeatedly. However, I do not investigate a row of multiple consequent choices (e.g., a first, second, and third related decision).

Finally, I focus on decision inertia in economic scenarios, because my aim is to provide design recommendations for robo-advisory or financial decision support systems. However, I explicitly avoid focus on decision inertia in incident scenarios (see e.g. (Alison et al., 2015)) or in disaster management. The decision-tasks in these kind of studies is too far away from the application of decision inertia in financial decision support.

4.1.1 Decision Inertia in Judgement and Decision-Making Research

The first relevant contributions of decision inertia research are the belief-updating tasks from the experimental psychology of the 60s, which reported an inertia effect or "resistance to change" (Pitz, 1969; C. R. Peterson & DuCharme, 1967; Brody, 1965; Pruitt, 1961) of decision-makers in sequential decision tasks. Other studies (C. R. Peterson & Miller, 1965; C. R. Peterson, Schneider, & Miller, 1965; Phillips & Edwards, 1966) reported that decision-makers have difficulty revising their subjective probability in an optimal amount (Geller & Pitz, 1968) and inspired other researchers to investigate this phenomenon in other settings (e.g. Kozielecki (1966)). Based on the findings from initial studies, researchers began to investigate possible explanations for this behaviour and focused on differences in confidence judgements compared to objective probabilities computed by the Bayes' theorem (Geller & Pitz, 1968).

One group of researchers focused on the inter-individual differences of errors, providing evidence that it underlays a systematic deviation (Little & Lintz, 1965). This so-called "conservatism bias" can be computed by comparing subjective with objective probabilities and could partly explain the deviations of future subjective probabilities from correct Bayesian probabilities (Little & Lintz, 1965). Others proposed to measure the decision-makers' conservatism by an "accuracy ratio", which is the ratio of subjective and objective log likelihood (C. R. Peterson et al., 1965).

Researchers such as Brody (1965) or Geller and Pitz (1968) investigated the effect of motivational drivers like commitment on inter-individual differences in confidence levels. Interesting findings are provided by Brody (1965). In their study, male children were asked to predict the most frequent word in a subsequent list of words (chose one of two). To measure the effect of commitment, the participants had to make a non-binding choice of one of two options, before they received any information (the control group did not choose before receiving information). The decisions were made under uncertainty: The participants did not know for sure which of the ratio of words was the actual one, but had to rely solely on the feedback after each decision. The results revealed that the initial decision of participants was associate with more confidence, as compared to the control group. Furthermore, if the decision was the less successful option, the confidence increase in subsequent decisions was lower. This finding suggest that decision-makers need more conviction to revise their option when a decision has been made. This need was stronger when they first decided randomly and without information upon the suboptimal decision - knowingly and willingly that the first decision was made without information and that they could revise their initial decision with no penalty.

Based on previous work, Geller and Pitz (1968) investigated decision speed in the context of inertia in belief-updating. In each of the trails, participants were asked to choose one of two "data-generating devices" (bags with poker chips) as a possible source of a sample of ten events. The participants were asked to predict the next chip (red or blue), and to guess which of the two bags the chip would be drawn from. For that purpose, they could adjust a toggle switch in the desired direction. The speed of the decisions was measured secretly. The findings show an increase in response time, if the event has been predicted by the participants, and a decrease otherwise. More interestingly, dis-confirming events did reduce the response time of the participants, but it did not reduce their confidence level. Geller and Pitz link this results to a commitment process and that the decision of the participants did not reflect their true opinions. In consequence, they suggest refusing Bayesian models as models of judgement and decision-making. However these initial findings provide further evidence, that human decision-making is driven by deliberative and intuitive processes (see Section 2.1). Consequently, decision inertia could be driven by the conflict of these different processes resulting in increased response times, and decreased decision speed.

Further studies investigating inertia were done by Pitz (1969); Pitz and Barrett (1969); Pitz, Downing, and Reinhold (1967). These studies provide further evidence, that a decision about the probability distribution of two hypothesis based on a sample of the length n is mainly driven by the time of the decision. The response differs depending on whether decision-makers are asked to judge after each draw of n, or at the end (Pitz, 1969; Pitz et al., 1967).

For instance, Pitz et al. (1967) examined the role of decision inertia in a simplified binary decision tasks. In the basic setting, two bags with a different number of red and blue chips were used. The participants could gather information about the distribution of the chips by drawing out balls. In this study, the participants were faced with a fixed sequence of 5, 10, and 20 samples from one of the bags. In each round they had to report their estimated probability that a certain bag was used. The estimates were compared to those predicted by the Bayesian Theorem. The findings indicate that subjective probability adjustments were greater following confirmation of information or short sequences, on the other hand long samples or dis-confirming information tend to increase the inertia effect.

Pitz proposed two possible explanations of inertia. Firstly, he proposed commitment as possible driver of inertia Pitz (1969); Pitz et al. (1967). He assumed that the participants commit themselves in their first decision, and hence all information that contradict the initial choice causes cognitive dissonance (Festinger, 1962). To reduce cognitive dissonance, decision-makers rely on inertia, and ignore or underestimate dis-confirming events. As a second explanation, Pitz proposed the expectancy-hypothesis (Pitz, 1969; Pitz et al., 1967). It is assumed that decision-makers expect dis-confirming information. Most decisions are made under uncertainty and the events are probabilistic. Hence, some events may be unlikely to occur, but occur nonetheless. Decision-maker assume that dis-confirming information about a state-of-the-world is not unlikely, but do not appropriately consider this possibility.

Related to these findings Pitz and Barrett (1969) conducted a further study, in which they varied the level of free information that participants could receive before deciding. The results suggest that less information was considered if the amount of free information increased, and hence riskier decision-making was more likely with increasing sample sizes.

In another study Pitz (1969) investigated the commitment process in sequential judgements. He replicated the belief-updating task from previous studies, but varied the levels of commitment to the previous decisions. If the previous decisions could be recalled easily, the participants showed the inertia effect. But under conditions, where the previous decision was not presented the inertia effect disappeared. Decision-makers without preliminary commitment showed no inertia effect (Pitz, 1969).

However, the findings of Pitz do not allow any conclusions to be drawn about the expectancy hypothesis. As Grabitz (1971) argues, the occurrence of early dis-confirming events reduced the diagnostic value of the dis-confirming events at high levels of individual confidence. Hence, assumptions about the size of the decision-maker's expectancy of a negative event are not credible. Geller and Pitz (1968) also report no support for the expectancy hypothesis.

Grabitz (1971) ran a variation of Pitz et al.'s study using one urn with different possible probability distributions. In the study, participants were asked to select between possible distributions and report their individual levels of confidence. As in previous inertia studies the participants received only a description of the different distributions, but they had to base their decisions on the feedback they received. To test the commitment hypothesis and the expectancy hypothesis against each other, Grabitz focused on decisions and confidence levels after the first dis-confirming events in a sequence of samples. If the commitment hypothesis is true, an early dis-confirming event would cause much more dissonance, than a late one. As a consequence decision-makers reduced their confidence in a decision significantly less, compared to when they faced a dis-confirming event at the end of a sequence of samples. Following this rationale, the expectancy hypothesis predicts the exact opposite. If decision-makers expect dis-confirming events, the probability of such an event will increase with the sample size. Hence, the later the event occurs, the stronger the influence on inertia. Testing these hypotheses against each other, Grabitz (1971) found evidence for only the first.

Based on these findings, Grabitz and Grabitz-Gniech (1972) conducted a further study based on a variation of his previous work (Grabitz, 1971); they investigated the commitment and conservatism hypothesis, and the expectancy hypothesis in context of the inertia effect. Their findings suggest that the inertia effect increased with the diagnostic information of an event, in line with the commitment hypothesis and contrary to of the expectancy explanation.

In order to clarify the relationship of existing results of reinforcement learning and decision inertia, Alós-Ferrer et al. (2016) used a variant of the task from Pitz (1969) and Charness and Levin (2005), which has been used by Achtziger et al. to show that the tendency of choice repetition or biased decision-making can be linked to increased response times (Achtziger & Alós-Ferrer, 2013). The variation of the task considers the assumption that decision inertia is a cognitive process that can conflict with other processes (e.g. Bayesian updating, or reinforcement). In their study, they conducted two variants of the urn game (decision inertia conflicting with Bayesian updating, or reinforcement). The participants were asked to make two subsequent decisions, and decision inertia was measured by choice repetition regardless of new information, and by response-time differences. They postulated that a process conflict would be linked to increased response times (slower decision-making). In line with previous findings (Achtziger & Alós-Ferrer, 2013), their results showed more errors and increased response-time in case of conflicting processes in both studies. However their findings hold only for free decisions (Alós-Ferrer et al., 2016, Study 2), indicating that decision inertia is stronger, or exists only in voluntary, autonomous decisions. If Bayesian updating and reinforcement conflict, they overload decision inertia.

Contradictory to Alós-Ferrer et al. (2016), Zhang et al. findings offer no support for the consistency hypothesis from Pitz. They investigated decision inertia in an ethical context (Zhang, Cornwell, & Higgins, 2014). In their study participants were faced with a two-stage decision task, where repeated cheating was measured. The study's findings suggest that decision repetition could be driven by prevention focus. Participants showed a significant increase in choice repetition in both cases, as a personal trait and induced by situation. Furthermore, alternative factors like choice justification were validated. However, the experimental setting from Zhang et al. (2014) is hardly comparable with the existing decision inertia research (e.g., it had a now outdated and different experimental design), and furthermore the moral framing could have influenced the decision-making process. Nevertheless, this early study provides evidence that results reporting commitment as a driver of choice repetition are not as stable as previously assumed. Presently, there remains a need to re-evaluate his findings in a more generalized decision inertia task (e.g. as in Alós-Ferrer et al. (2016)).

More evidence for motivational drivers of decision inertia comes from Sautua (2017), who investigated the influence of regret aversion and indecisiveness on decision inertia in subsequent lottery-ticket-switching-tasks. In his study, the participants randomly received one of two tickets for a lottery. In the next step, they could choose to switch the ticket for a small pay-off. Decision inertia was measured as the tendency to keep the perceived ticket, regardless of the pay-off and the probability distribution of the lottery. By changing the degree of uncertainty of the lottery, or the option to switch tickets Sautua showed that the participants had a tendency to rely on the previous decision (lottery ticket they received). Both regret aversion and indecisiveness had significant influence on decision inertia. But regret aversion had only a significant effect, though only if the participants did not know they would have the option to switch tickets. However, the study of Sautua is rarely comparable to existing belief-updating tasks like the study from Alós-Ferrer et al. (2016), the experimental setting is quite different. However, his findings do suggest that further motivational variables are relevant drivers of decision inertia. Furthermore, it suggests that regret aversion can be a possible source of decision inertial behaviour, but in this case decision inertia is co-founded with reluctance or the distrust towards the experimenter which offers the option to switch.

Other research did not investigate decision inertia explicitly, but their studies contains evidence for the decision inertia phenomenon and their findings provide many interesting implications for the decision inertia research. The most relevant studies of this kind are Charness and Levin (2005), and Achtziger and Alós-Ferrer (2013). Charness and Levin (2005) report that "a person who has elected to make the first draw from left is substantially more likely to make the second draw from Left [sic!] than a person who was required to make the first draw from Left [sic!]" (Charness & Levin, 2005, p.1305). Their study, which was a replication of existing methods from experimental psychology and Bayesian updating (see e.g. Pitz (1969); Brody (1965)), is the first that reported clearly that decision inertia could be linked to the autonomy of a decision. They investigated the ways in which decision-makers rely on Bayesian updating after successful and after unsuccessful outcomes of a decision after free and required choices. In their task, the participants had to choose between two urns with two different states and the probability distribution of the pay-offs (two choices task). The participants had to choose freely or were forced, alternately. As in previous belief-updating tasks the first round could be used to learn about the state of the world and to make subsequent optimal or suboptimal decisions based on Bayesian theorem. By comparing different factors with the number of decision-makers to update prior beliefs in the context of Bayesian theory, they could test the influence of these variables on belief-updating. Charness and Levin reported that if the first decision was not rewarded (e.g., affect removed in first round), the participants made significantly fewer errors, which provides further evidence that decision inertia could be linked to commitment or at least to a kind of mental coupling of previous decisions. This finding is in line with the findings of Brody (1965), who reported that no commitment had significant influence compared to forced commitment in the first round of a subsequent decision task.

Other indirect evidence for decision inertia comes from Achtziger and Alós-Ferrer (2013). Achtziger and Alós-Ferrer investigated response-time in relationship to Bayesian Updating. The findings suggest that decision inertia exists, and they report an increased tendency to repeat a decision regardless of the consequences (see Table 1 in their study; decision inertia or loss-stay errors: 38.9 and 25.1 %). Furthermore, the study reports an increased response time in the case of decision inertia (response time after a loss), but also in the case of general process conflicts. An interesting finding is that neutral situations involve longer response times than alignment (in particular, decision inertia with Bayesian Updating and treatment ALIGN; see Table 2 in their study).

Erev and Haruvy (2013) review recent literature in economic decision-making and propose a descriptive model "Inertia, Sampling and Weighting" that can be used to reproduced economic decision-making. Their model assumes three response modes: exploration, exploitation and inertia (Erev & Haruvy, 2013). Inertia is defined as the individual's tendency to repeat choices, and decreases when the outcome of a decision is surprising. Following this reasoning, Erev and Haruvy conceptualize decision inertia as a trait that is stable over the time, but the probability to rely on depends on the outcome of a decision.

Table 9: Selection of the most relevant findings from studies investigating decision inertia or relevant aspects of decision inertia in judgement and decision-making research.

Authors	Sample	Definition	Findings
Alós-Ferrer et al. (2016)	Students from the University of Cologne (study 1: n=45, 16 males, M=23.51 years; study 2: n=44, 19 male, M=23.80 years)	"the tendency to repeat a previous choice, regardless of its outcome, in a subsequent decision." (p.1-2)	**Considered factors:** Decision autonomy (free vs. forced decisions), preference for consistency, Bayesian Updating, Reinforcement **Results:** They assume that decision inertia is a "cognitive process" potentially "conflicting with other processes" (e.g. Bayesian Updating, Reinforcement). They find evidence that decision inertia exists in forced and free decisions conflicting with Bayesian Updating, and in free decisions conflicting with reinforcement. Furthermore, they find learning effects (round number significantly negative influence on decision inertia). If Bayesian updating and reinforcement conflict, they dominate decisions inertia, indicating that decision inertia can be overloaded by stronger processes. Furthermore decision inertia is associated with increased response times and preference for consistency, which is in line with a dual-process perspective on decision inertia.
Brody (1965)	Princeton high school boys (n=72, 72 males, M=16.1 years)	Na	**Considered factors:** Initial commitment without information, confidence **Results:** Initial commitment is related to increased initial confidence, but does not influence the time of a decision. If participants committed to an incorrect decision, they increased confidence more slowly than the control group without an initial commitment, or the group which committed to a correct decision. Additionally, incorrect initial commitment results in lower confidence in the final decision.

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Table 9 – *Continued from previous page*

Charness and Levin (2005)	Students from the university of California (Study 1: n=59, Study 2: n=54, Study 3: n=52)	"taste for consistency" (p.1305)	**Considered factors:** Reinforcement, Bayesian updating, decision autonomy, affect **Results:** When intuitive and deliberative processes conflict (e.g., reinforcement and Bayesian updating, switching after a loss) the error rates are significant larger, compared to when the processes are aligned. The aggregated drawings show that the participants had a tendency to repeat previous decisions (regardless of the pay-offs), covered by the decision inertia hypothesis. If the first round was without pay-off or the participants were forced to choose one of the two urns randomly (only for the first decision), the errors were reduced. On the other hand, when the information of the first round was increased, the error rates did not change. Besides, the findings report positive influence of gender (female) and choice complexity on errors; and no learning effects.
Geller and Pitz (1968)	Students from the southern Illinois university in context of an experimental psychology course (n=22)	"failure to reduce confidence following dis-confirming events" (p.194)	**Considered factors:** Decision speed, confidence **Results:** An increase in decision speed is linked to predicted and confirming events, while dis-confirming events resulted in slower decision-making and suboptimal confidence revision. Surprisingly, dis-confirming events did reduce response time, but did not reduce the confidence level.
Grabitz (1971)	Students from the university of Mannheim (n=36)	"underestimation of those events, that are contradictory to a subject's presently favored alternative" (p.35)	**Considered factors:** Commitment, expectancy **Results:** The findings support the commitment, but not the expectancy hypothesis. The participants did estimate the probability more correctly compared to the confirming events the later the dis-confirming event occurred. This finding is in line with the commitment hypothesis, which predicts an decrease in overestimation; but contradictory to the expectancy hypothesis that predicts an overestimation. Decision time was slower after dis-confirming events.

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Grabitz and Grabitz-Gniech (1972)	Students from the university of Mannheim (n=42)	"Informationen mit gleichem diagnostischen Wert, wurden verschieden bewertet, je nachdem, ob sie die subjektive Wahrscheinlichkeit der Person erhöhten oder senkten" (p. 25)	**Considered factors:** Commitment, conservatism, expectancy **Results:** The relative underestimation of probabilities increases with the diagnostic value of an event. The differences in the accuracy ratio indicate that conservatism is not the only driver. Furthermore, the higher the diagnostic value of a dis-confirming event, the more likely it is to be underestimated, in other words, strongly dis-confirming events are more likely to be perceived as wrong, than are weak dis-confirming events.
Pitz (1969)	Participants (n=75, 15 per treatment)	"reluctance of Ss [subjects] to reduce their confidence in a decision following disconfirming information." (p. 24)	**Considered factors:** Presentation of previous judgement (visual, verbal, none), physical movement (user interface), preliminary confidence judgement **Results:** Decision-makers decide differently if they have to decide sequentially compared to tasks in which they have to decide at the end of a sequence of information. When the participants could easily recall the previous judgement, the inertia effect increased. If previous judgements are not presented, the inertia phenomenon does not exist. The findings provide evidence for a "resistance to reversal" instead of commitment.
Kozielecki (1966)	Na	Na	**Considered factors:** Self-confirmation, confidence, hypothesis threshold **Results:** Reaction to new information does not depend on the threshold at the moment the first decision. Participants of his study had a tendency to not adjusting their individual certainty in a hypothesis after disproving conflicting messages.
Sautua (2017)	Student sample from university of California, Los Angeles (n=346, about 50 per treatment)	"the tendency to adhere to the status quo" (p.14)	**Considered factors:** Regret aversion, indecisiveness **Results:** Regret aversion and indecisiveness are linked to decision inertia. When participants knew that they could switch tickets, the influence of regret aversion disappeared. On the other hand, if the participants did not know that they could switch tickets, the inertia effect increased.

Another stream of decision inertia research is from occupational and organizational psychology. The most popular pioneers in this area are Alison and Power, who investigated decision inertia in a number of real-world settings (Power & Alison, 2017; Alison et al., 2015; Eyre, Alison, Crego, & McLean, 2008). However, their understanding of decision inertia differs from that of the majority of existing decision inertia research studies. In particular, they follow the naturalistic decision-making paradigm and neglect the existence or the labelling of decisions as "right or wrong". They focus on the understanding of the cognitive process in real-world scenarios (Power & Alison, 2017; Alison et al., 2015). As a consequence, deviations from rational strategies are not computed or can not be identified. In this research stream, the researcher conceptualizes decision inertia as a more general concept, namely the "inability to reach a decisions" (Alison et al., 2015). Following their conclusion, decision inertia is linked to redundant information-seeking and choice delay or avoidance. All their studies investigate decision inertia in critical incidents, which makes their work hardly comparable that of other research streams. Additionally, the approach makes it impossible to reproduce the findings in experimental settings, a further major difference from contemporary research. Even if their work might offers insights into the phenomenon of decision inertia at a more general level, in the context of loss framing or indecisiveness, there remains a need to investigate the way in which and degree to which their findings can be linked to the main stream of decision inertia research. As a consequence, this research stream is excluded in the further investigation (see Section 4.1).

4.1.2 Decision Inertia in Neuro-Science Research

Since the decision inertia phenomenon is well-known in judgement and decision-making research, it is somewhat surprising, that decision inertia has been treated for a long time as a random process or as noise in many studies of human decision-making (Akaishi et al., 2014; Gold et al., 2008; Corrado, Sugrue, Seung, & Newsome, 2005), even in the decision-making of monkeys (Lau & Glimcher, 2005). However the neural foundations and brain mechanisms involved in decision inertia remain unknown, and there remains a need to identify and classify the correlates of decision inertia (Fleming, Thomas, & Dolan, 2010).

Recent neuro-science research has targeted this gap, raising discussion of this process as relevant to the understanding of our decision-making and that individuals vary systematically in their sensitivity to decision inertia. In fact, a recent fMRI study reports that decision inertia reflects a systematic, autonomous mechanism that can be modelled by learning rules (Akaishi et al., 2014). Consistent with Akaishi et al. (2014), such studies suggest that decision inertia is an unconscious process and probably strongly dependent on prior decisions. In his study Akaishi et al. investigated possible explanations for the tendency of decision-makers to rely on previous decisions in decision-making, even when they are asked not to do so or plan not to do so. The participants played a variation of the two-direction motion discrimination task from Gold and Shadlen (2007), where they had to identify the motion of a group of dots with little sensory evidence. The findings speak against the assumption that decision-makers' tendency to rely on previous decisions can not be modelled by response bias, sensory bias or attention bias (Akaishi et al., 2014). Decision inertia could be observed in delayed-response decisions, as well in decisions with four options. Participants' tendency to rely on decision inertia increased after dis-confirming results or errors in previous decisions, and a decrease of sensory evidence. Because the participants received no immediate feedback, Akaishi et al.

argue that decision inertia could depend on a specific process of error making and not on the capabilities to detect that an error has been made.

Other learning models have also included decision inertia in their considerations. For instance, Gonzalez and Dutt (2011), and Gonzalez, Dutt, and Lejarraga (2011) integrated an inertia mechanism in their models. In general the findings suggest that including inertia in instance-based learning models increases predictive power. A review of Dutt and Gonzalez (2012) comparing different learning models with and without an inertia parameter with a popular dataset as a baseline, supports this suggestion. Although, models with inertia may be better in behaviour prediction, they are not superior in modelling trends across different tasks, and they do not persist in decisions without payoffs (Dutt & Gonzalez, 2012). Findings from Lejarraga et al. (2012) show that certain instance-based learning models can predict risk-taking in the binary-choice tasks without an inertia factor. However, computational models require such a mechanism to explain observed risk-taking and alternations (Dutt & Gonzalez, 2012). As a consequence, there is evidence from learning modelling that such inertia mechanism may be a relevant factor in explaining human decision-making.

Based on the work of Grether (1980, 1992), who investigated heuristic decision-making in Bayesian belief-updating task, Achtziger, Alós-Ferrer, Hügelschäfer, and Steinhauser (2012) investigated the influence of conservatism and over- or underestimation of subjective beliefs on new information in an Electromyography (EMG) study. The results of the lateralized readiness potential indicates that conservative decision-maker have a tendency to immediately rely on priors, before new information can even be processed. This tendency rules out previous explanations of the underestimation of new information by conservative decision-makers in belief-updating tasks, like errors in aggregation of prior (Edwards, 1968), information retrieval (Dougherty, Gettys, & Ogden, 1999), or the avoidance of extreme decisions (DuCharme, 1970; Achtziger et al., 2012). Furthermore, Achtziger et al. observed increased response time in conflicting situations, providing further evidence for the dual-process perspective of intuitive and deliberative processes in belief-updating tasks.

Another study of Fleming et al. (2010), investigated neural correlates of the tendency to rely on, or to switch away from the status quo. In visual determination tasks, the participants had to decide whether a tennis ball was in or out. After each visual stimulus two options were presented, with one of the options set as default. An increase in task difficulty could be linked to increased likelihood to rely on the default option. Furthermore, activity in the subthalamic nucleus and in the frontal cortex increased when participants switched away from the status quo.

Table 10: Selection of the most relevant findings from studies investigating decision inertia or relevant aspects of decision inertia in neuro-science research.

Authors	Sample	Definition	Findings
Achtziger et al. (2012)	Students from the university of Konstanz (n=25, male=13, M=21.8)	Na	**Considered factors:** Bayesian updating, conservatism, base-rate neglect, representativeness heuristic, electro-cortical activity **Results:** Deviations from the Bayesian rule can be linked to electro-cortical activity. Lower sensitivity in conflict detection could be linked to participants with a tendency to overweight new information, while a Lateralized Readiness Potential (LRP) in the brain could be linked to participants under-weighting new information. The results suggest that conservative decision-maker do notice new information, but have a tendency to immediately rely on the prior in decision-making, resulting in a decision before the new information has even been presented.
Akaishi et al. (2014)	Participants at the university of Tokyo (study 1: n=14, M=27.1 years; study 2: n=11, M=26.5 years; study 3: n=20, M=25.4 years; study 4: n=15, M=25.3 years; study 5: n=14, M=23.4 years; study 6: n=17, M=25.5 years; screened for neuropsychiatric disorders)	"tendency of choice repetition" (p.195)	**Considered factors:** Information ambiguity, neural activity, 2 vs. 4 choice options, choice delay **Results:** Intermediate and low ambiguous information results in more decision inertia, does than unambiguous information. The effect is stable in two-choice, four-choice, and delayed-response tasks. Errors in previous decisions, have resulted in an increased error rate in the next decision. Motor response bias, sensory bias, and attention bias were excluded. Activation in the neural regions medial parietal cortex, posterior cingulate cortex, and putamen are linked to decision-inertial behaviour. Activation in the right frontal eye field could be linked to correct decision-making.
Dutt and Gonzalez (2012)	100 participants (secondary data from Technion Prediction Tournament (TPT) dataset (Erev et al., 2010))	"tendency to repeat the last decision irrespective of the obtained outcomes while making decisions from experience" (p.1)	**Results:** Different learning models with and without an inertia parameter are compared on the TPT dataset. Models with inertia are better in behaviour prediction, but not in modelling trends across tasks.

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Yu, Mobbs, Seymour, and Calder (2010)	Volunteers (study 1: n=18, 8 males, M=22.4; study 2: n=15, 6 males, M=24.6; screened for neuropsychiatric disorders)	"choosing the default" (p.14702)	**Considered factors:** Neural activity **Results:** If there is a default option, decision-makers have a tendency to rely on it. The FfMRI reports that the tendency to rely on the default is linked to fewer emotional responses to the outcome and activity in the ventral striatum, while the decision to switch away from the default was linked to decreased activity in the anterior insula and frustration experienced. Yu et al. (2010) conclude that choosing the default is linked to self rewarding processes.

Another general but relevant finding for decision inertia research is provided by Achtziger, Alós-Ferrer, Hügelschäfer, and Steinhauser (2015). In their study Achtziger et al. compared the influence of monetary incentives and reinforcement by immediate feedback on performance in decision-making, a finding also reported by Grether (1980). The hypothesis is that the relationship between performance and monetary incentivisation is non-linear, and can thus be influenced by reinforcement processes. In particular, Achtziger et al. assume that reinforcement in combination with increasing incentives is linked to more errors in decision-making. It is argued that the salience of the win or loss of the previous decisions results in more reliance on non-rational decisions. Or in other words, because of the immediate feedback, the decision-makers tend to consider only the last outcome of their decisions, which can lead to more errors if reinforcement and rational behaviour conflict. The conflict between rational decisions and reinforcement was induced by a replication of the task from Charness and Levin (2005). In the second study, the affect of the first decision was removed by paying only the second decision, and forcing the decision-makers to always pick the left urn in the first decision. Furthermore the event-related potentials of the participants was measured with an Electroencephalography (EEG). The results of the two studies report no significant influence of monetary incentives on performance, but a correlation of neural correlates of reinforcement learning (feedback-related negativity amplitudes, 200-300 ms after the feedback) with errors in decision-making (Achtziger et al., 2015). In the low-incentive treatment, no correlation appeared between the neural correlates and errors. By removing the affect (Study 2), increased incentives were linked to increased performance. This finding is in line with other studies which provide evidence that high incentives can cause non-rational decision-making (Chib, De Martino, Shimojo, & O'Doherty, 2012), (Mobbs et al., 2009), suggesting that decision inertia might depend on the incentivation, and the salience of the reinforcement process (see (Alós-Ferrer et al., 2016)).

Moreover, Cockburn, Collins, and Frank (2014) have also investigated decision-makers' tendency to prefer freely chosen options above options without alternatives. His findings could link biases to inter-individual differences in reward learning and dopaminergic striatal plasticity. Differences in the DARPP-32 gene could be identified as possible drivers of this behaviour, indicating that bias could be driven by credit assignment that delivers the dopaminergic reinforcement learning signals to the striatum (Cockburn et al., 2014). However, the findings hold only for rewarded decisions, not for unrewarded decisions.

Further substantial findings comes from trial-history research. Recent findings from neuro science experiments suggest that sensory stimuli discrimination is biased by method of stimulus or cue presentation, and previous decisions (Kaneko & Sakai, 2015). Hence, this could have implications for decision inertia, because decision inertia tasks pose a history of decisions for participants. For instance Kaneko and Sakai (2015) conducted a visual target detection task, where the participants had to confirm the presence or absence of sine-wave gratings on a screen. Before each experimental stimuli the experimenter gave a cue as to the probability that a motion would appear. The results show a significant influence of the probabilistic information and the decision of the previous trial (even if the trials are independent, and if the participants know that). Kaneko and Sakai (2015) summarize that the reason remains unclear because the mechanism could be driven by three sources: the previous stimulus, decision, or response. Other studies report similar findings, and suggest that this mechanism also drives the processing of sensory information (Gold et al., 2008; Liston & Stone, 2008; Bode et al., 2012). However, even if the reasons for this phenomenon remain open, a possible reason for this behaviour is decision inertia. If decision-makers have decision inertia, they will rely on previous decisions, and this reliance could explain the observations.

4.1.3 Decision Inertia in Information Systems Research

In information systems research, decision inertia has been used in various studies and behavioural models to "explain the resistance to change from a status quo" Polites and Karahanna (2012). The existence of decision inertia has been linked to different individual dispositions, and has been explained by motivational factors. However, the understanding of this mental process in information system research remains relatively modest at the moment, although it holds much potential for the explanation of information systems adoption and innovation resistance.

Jermias (2001) investigated the influence of commitment and feedback on resistance to accepting a new accounting system. In his study, 89 participants were assigned into four groups (2×2 full factorial design). The results show a significant influence of commitment to the valuation of the system: in particularly, committed participants rated the chosen system better than non-committed participants. However if they received negative information about their decision, the participants rated the system worse than did non-committed participants. Furthermore, commitment could be linked to increased decision inertia, regardless of the feedback. In the positive feedback condition both groups showed an increase in inertia, and did not differ significantly. However, these findings are in line with studies from judgement and decision-making research indicating that loss or win framing can influence individuals' tendency to rely on decision inertia. Hence, it might be possible that the feedback drives decision inertia and as a consequence, that resistance to change increased.

A comparable study has been done by Polites and Karahanna (2012). Their work, has investigated the influence of inertia, habit, and switching costs on system acceptance and their inter-relationship. For that purpose, Polties and Karahanna conducted a survey with about 600 students. An inertia scale was developed and participants were asked to fill it out together with other items. The results show that the adoption of new systems is caused by habitual use of the old system, rational considerations about the switching costs, and psychological commitment due to consistency-seeking. Inertia is linked to increased ease of use, and usage intention.

Based on this conceptualization of inertia, further studies investigated the acceptance intention and referred to inertia, which illustrates the benefit or need to integrate such a factor in user-acceptance models. For instance, Chowdhury, Islam, and Rana (2016) relied on inertia in their model describing the influence of consumer attitude towards mobile advertising. They developed a conceptual model of consumer advertising attitude, and evaluated it with students in Bangladesh. The results suggest that inertia has a negative and significant "influence on consumer attitude towards mobile advertising" (Chowdhury et al., 2016).

Another study relying on decision inertia to explain resistance to change is from Li et al. (2016). Their investigation focuses on the acceptance of knowledge-management systems.Their study, investigated the introduction of a new knowledge management system of participants of a Chinese petrochemical company was investigated. Data was collected with a survey with participants containing questionnaires about loss aversion, transition costs, social norms, and inertia. The results suggest that inertia has an interaction effect with the other factors, and drives the resistance of the new systems. This provides evidence, that inertia is also driven by situational and contextual factors. Park (2016) has reported similar findings. In his study, the updating behaviour of mobile application users was investigated, and the results suggests a significant negative influence of inertia on willingness to update.

Table 11: Selection of the most relevant findings from studies investigating decision inertia or relevant aspects of decision inertia in information systems research.

Authors	Sample & Design	Definition	Findings
Jermias (2001)	Students of the university of Waterloo (n=89)	"resistance to change" (p.146)	**Considered factors:** Dissonance, commitment, confirmation, feedback **Results:** Participants who choose one of the two systems by themselves were significantly more likely to rely on decision inertia compared to non-committed participants. Furthermore positive feedback could be linked to increased inertia, while negative feedback decreased inertia effect. This effect did not differ for the commitment group as compared to the non-commitment group when the feedback was positive, but the effect was significant different for negative feedback.
Li et al. (2016)	Employees of a petrochemical company in China (n=982)	"inertia is defined as user attachment to, and persistence in, using an incumbent system, even if there are better alternatives or incentives to change [...] consisting of three components: affective inertia, behavioural inertia, and cognitive inertia" (p.193-194)	**Considered factors:** Loss aversion, transition costs, social norms **Results:** Inertia has a significant interaction effect with loss aversion, transition costs, and social norms on inertial behaviour (resistance intention). This effect indicates that situational factors like a company where losses are heavily sanctioned can act as driver of decision inertia.
Polites and Karahanna (2012)	Students from a university in the southeast of the United States	"user attachment to, and persistence in, using an incumbent system (i.e., the status quo), even if there are better alternatives or incentives to change." (p.24)	**Considered factors:** Habit, switching costs **Results:** The adoption of a new systems is caused by habitual use of the old system, rational considerations about the switching costs, and psychological commitment due to consistency-seeking. Inertia is linked to increased ease of use, and to usage intention.

Another very interesting approach is from Stryja and colleagues (Stryja, Dorner, & Riefle, 2017; Stryja, Satzger, & Dorner, 2017). They propose to reduce decision inertia by system design in decision support systems. In their studies, they investigate different nudges to overcome the tendency of decision makers to rely on decision inertia in the case of electric car adoption. Drawing from organizational change and the psychology literature, they propose priming and defaults to reduce decision inertia. Firstly, the priming effect builds on recency considerations.

If the positive aspects of an option are presented shortly before the decision, the decision-maker will be more to likely rely on that option. In the second case, decision inertia is linked to the optimal choice, and as a result the negative consequences of decision inertia are removed. So far, this work is the first approach targeting the reduction of the effects of decision inertia by system design and provides interesting insights. However, the work is still in progress and the final results of their investigations are not yet available.

In sum, one main finding of the information systems literature review is that decision inertia is mostly measured by self-reporting data and not by objective measurements in the lab. This methodological tendency is a main difference from judgement and decision-making research, and from neuro-science. In particular, this difference raises the question of whether the constructs are comparable and reliable across the tasks and disciplines. Furthermore, it is questionable whether the participants answer truthfully. For instance, it remains unclear whether the perceived behaviour (measured e.g. by NeuroIS methods like EEG), the actual behaviour (measured e.g. with click-stream logging), and the reported behaviour (measured e.g. by questionnaire) are the same.

The division of inertia into three sub-scales, as proposed from Polites and Karahanna (2012), has been generally accepted, but so far this has not been sufficiently explained and is only vaguely linked to existing findings from judgement and decision-making. As a consequence there remains a need i) to test and investigate the relationship of actual decision inertia with the inertia scale from Polites and Karahanna, and ii) to clarify whether the partition, number and clustering of inertia into the three parts affect, behaviour, and cognitive based inertia is reliabl and useful. This question is especially pressing, considering the finding that other studies could not replicate the intern-consistency of the scale in other settings (see e.g. Li et al. (2016)).

Furthermore, information systems studies focus exclusively on the intention to adopt, or the resistance to change respectively. The main purpose of this work is to understand and investigate the drivers of decision-repetition, though and not the manifestation (resistance to change, or status quo) of this process. In particular, this work concentrates on decision inertia in subsequent decisions, where the reasons why people rely on decision inertia remains unclear. Recent information systems research does not address this area of focus. Rather, it investigates inertia relying on a more generalized conceptualization and understanding, but ignoring the underlying mental processes. For instance, Polites and Karahanna (2012) argue that specific factors can increase the behavioural consequence of decision inertia (e.g. transaction costs are a rational argument for decision-maker to behave inertial). This argument seems reasonable, but in this work I try to understand why decision-makers rely on inertia even if its *not* rational, especially why it occurs regardless of the consequences.

4.1.4 Distinguishing Decision Inertia from Other Related Terms and Concepts

The previous theoretical background section has illustrated that there exists a broad conception of decision inertia in judgement and decision-making research. This variance makes the investigation of decision inertia and the identification of relevant work a difficult endeavour. Furthermore, decision inertia and decision inertial behaviour has previously been studied under various other labels. There exists a wide range of loss aversion and avoidance biases and phenomena that may have a conceptual overlap with decision inertia. As a result, there remains a need to further clarify the concept of decision inertia.

Decision Avoidance: The concept of decision avoidance as a general umbrella term for biases resulting in non-decisions, proposed by Anderson (2003). He reviewed studies of avoidance biases and phenomena in judgement and decision-making literature, discussing possible drivers of choice deferral, inaction inertia, omission bias, and status quo bias as the driving forces behind human decision avoidance. As a result he has generalized these findings in a model of a "psychology of doing nothing", postulating that decision avoidance is caused in particular by anticipated regret, and selection difficulty (Anderson, 2003). Although, this finding might be useful in explaining and investigating other decision biases, it remains open whether this assumptions hold for decision inertia. He supposed relations of the drivers have been derived from a literature review, and they lack an experimental validation. Alison is more clear, positing that decision inertia "is distinct from decision avoidance (Anderson, 2003) where decision-makers refuse to evaluate choice through passive inaction (e.g., 'I choose not to decide for the time being'). Instead, I have observed how decision-makers fail to act through 'decision inertia'" (Alison et al., 2015).

Status Quo and Omission Bias: One of the most common biases related to decision inertia, is the status quo bias (and its sub-aspect omission bias (Ritov & Baron, 1992)). The status quo bias is based on the assumption that a "decision maker in the real world may have a considerable commitment to, or psychological investment in, the status quo option" (Samuelson & Zeckhauser, 1988, p.10), while the omission bias postulates that the status quo bias captures the tendency to decide in favour of the option which requires the least action. Both biases suggest that the decision-maker shows a behaviour, which can be similar to that of decision inertia (repeating a suboptimal decision without considering the consequences). However, decision inertia is not status quo bias, even if it may manifest in some situations as a tendency to favour the status quo. One argument for of differentiating between decision inertia and status quo bias is the fact that in many decision environments for decision inertia research do not contain a current state, no status quo option, and both options are linked to action (see e.g. Alós-Ferrer et al. (2016), Charness and Levin (2005)). Thus, when decision-makers in such environments exhibit inertia, the underlying process cannot be related to status quo bias but rather to a tendency to repeat previous decisions regardless of the consequences. Consequently, in many studies participants cannot rely on status quo bias, despite that they show a tendency to repeat their previous strategy. Another argument for distinguishing the two concepts is provided by the experiments of Maltz, Romagnoli, et al. (2015), illustrating further evidence against the current conceptualization of status quo bias in judgement and decision-making research, per se. In a series of experiments, Maltz and Romagnoli investigated the status quo bias in risk-setting and under changing ambiguous conditions. They conclude that status quo bias disappears in games where both alternatives are risky, or both ambiguous (Maltz et al., 2015). These findings agree with those of with other studies, which postulate that "inertia acts like a status quo bias" (Dutt & Gonzalez, 2012, p.1), consequently I argue that decision inertia it offers a promising path to explain the mixed findings regarding the status quo bias, because it is one part of the underlying process driving the observed status quo tendency of decision-makers.

Habit: A habit is an "attachment to, and persistence of, existing behavioural patterns (some of which are habituated) even if there were better alternatives and incentives to change" (Polites & Karahanna, 2012, p.22). This definition assumes that decision-maker can rely on habits they have built in judgement and decision-making. Most decision inertia studies (see Section 4.2), rely on subsequent, tasks to measure decision inertia, where it seems not possible that decision maker could have enough time to build habits (which typically takes multiple days or weeks). Accordingly, Polites and Karahanna (2012) reason that inertia and habit must be considered differently in research, because habits are learned responses that are triggered automatically, hence it may be that inertia is driven by other factors.

Endowment Effekt: This bias describes the tendency of decision-maker to estimate the value of something to be greater if they own that thing (Kahneman, Knetsch, & Thaler, 1990). Thus, one could argue that decision inertia is partly explained by overestimation. However, this claim might not fully explain decision inertia, because decision inertia is about repeating decisions, not about appreciating a good. Moreover, the different experimental designs do not suggest that the participants had a feeling of ownership because they choose between different strategies, urns and so on. Furthermore, participants typically value both options the same at the outset of a study of decision inertia (showing no endowment). Hence, if at all, biased probability estimation by the participants could be a possible explanation. In addition, studies on the endowment effect suggest that the effect is driven by different references points (Carmon & Ariely, 2000), which are not of explanatory value in current decision inertia studies.

Choice Deferral: Describes the tendency of decision-makers facing a difficult decision to make no choice at all (Dhar & Nowlis, 1999). Consequently, a decision-maker facing a difficult decision without a defer option, would probably select a random option. This option can also be the previous decision, which than is equal to decision inertia. In such a case, decision inertia and choice deferral behaviour would probably overlap. However, this kind of behaviour would also mean, that other types of errors increase in such scenarios, because the decision-maker chooses randomly. This possibility has not been observed in decision inertia research. Furthermore, decision inertia and choice deferral can be separated into distinct outcomes if a no-decision option were provided. I did this in Section 4.4, and found no significant influence of this feature on biased decision-making. Hence, it seems reasonable that decision inertia and choice deferral might have shared drivers, but they are distinct biases caused by different factors.

Inaction Inertia: Another phenomena that has some behavioural overlap with decision inertia is inaction inertia. Inaction inertia is definied as "when bypassing an initial action opportunity has the effect of decreasing the likelihood that subsequent similar action opportunities will be taken" (Van Putten, Zeelenberg, van Dijk, & Tykocinski, 2013, p.1). In particular, inaction inertia has great implications for marketing, as it suggests that discount campaigns increase willingness to buy in the short term, but reduce the willingness to buy when they expire. Customers who learn about the campaign afterwards are no longer interested in the product. Furthermore, inaction inertia can influence the behaviour of investors who missed the option to switch strategy in a market (Tykocinski, Israel, & Pittman, 2004). The central difference to decision inertia is that the experimental paradigms that generate inaction inertia presuppose an opportunity has been missed and that the circumstances have changed. Furthermore, the participants do not choose by themselves, they are always presented a short text describing their past actions. Hence, they never really "make" a first decision. Decision inertia tasks do not use this kind of mindset. In their tasks, participants choose between options, which stay the same across the whole experiment, as the probability distributions and outcomes. Furthermore, participants make real decisions, and are generally not faced with descriptions what they have done or will do. Thus inaction and decision inertia can have the same behavioural consequence in specific cases, but different cognitive processes can be assumed here.

Indecisiveness: Indecisiveness is decision-makers' inability to make a decision in a timely manner across situations and domains (Frost & Shows, 1993). It is a personal trait used in diagnostic psychology to predict behaviour across many domains. In the context of decision inertia, it is possible that individuals who experience more indecisiveness will have a greater likelihood of repeating previous decisions regardless of the consequences. In this case, indecisiveness assumes that decision-makers show decision inertia when they are indecisive. Following this hypothesis, decision inertia is therefore caused by an evasion of a decision or responsibility for it. It seems possible that this might explain different aspects of decision inertia, so, I examine that relationship in more detail in Section 4.4.

4.2 Measuring Decision Inertia in a Dual-Choice Paradigm

In judgement and decision-making research, there exist various approaches to measure the behavioural or cognitive outcomes of decision inertia in experimental tasks (see, Tables 9, 10, and 11). A deeper investigation of these tasks shows, that the distinct streams investigate *behaviour as a proxy for the manifestation of decision inertia* under very different circumstances, for example decision inertia after reception of visual information (Akaishi et al., 2014), decision inertia as a failure in belief-updating (Alós-Ferrer et al., 2016; Charness & Levin, 2005) and confidence in beliefs (Pitz & Barrett, 1969; Geller & Pitz, 1968; Pitz et al., 1967), as an increase in response-time (Alós-Ferrer et al., 2016; Achtziger et al., 2012), or as reluctance to switch away from an option after information (Dutt & Gonzalez, 2012), as tendency towards choice repetition in economic risk games (Erev & Haruvy, 2013; Erev et al., 2010) and so on. As a consequence, the measurement of decision inertia varies widely, and it remains unclear whether the same results hold in other experimental settings, and if whether they are generalizable at all.

Thus, I present a neutral and reliable setting to induce and reproduce decision inertia. Furthermore, this paradigm allows one to vary the possible drivers of decision inertia easily. For that purpose, I offer a short overview of the most relevant tasks of recent decision inertia research, and discuss their practical value for further decision inertia research. Finally, I summarize recent decision inertia tasks, and based on these findings I derive a framework (dual-choice paradigm) for the analysis of decision inertia for subsequent decisions in the lab.

4.2.1 Operationalization of Decision Inertia

Many papers have induced and measured decision inertia in experimental tasks in the lab, while some studies have measured inertia-related behaviour (but not decision inertia itself) through questionnaires (see Table 12). Furthermore, they differ in their understanding and timing of the decisions. In the decision tasks, there are two ways to conceptualize decision inertia: *subsequent* and *sequential*. Under the first condition, the participants are faced with two subsequent decisions and decision inertia is mostly measured by the tendency to rely on the first decision. In the sequential version, the participants repeat a decision n times. The value of n can be represented as many times as they want to repeat the decision, or it can be represented a fixed number of draws.

The most common approach of sequential decision inertia tasks in the lab is based on belief-updating tasks from Pitz (1969); Pitz and Barrett (1969). These tasks focus in particular on reluctance to update beliefs in sequential decisions. In these studies, participants are usually given the task of reviewing the likelihood of a given set of decision alternatives based on information or a continuous series of pieces of information, if necessary, selecting one of the options. The probabilities of the two options are usually equally likely at the beginning. These studies have shown the inertia effect (e.g., the participants underestimate, specifically the impact of contradictory information on their decisions). These tasks allow the measurement of the inertia effect within a subject in a series of task, and they enable one to measure other correlates like response time or arousal, making conclusions about the conditions and situations, in which decision inertia is likely to occur.

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Table 12: Experimental tasks from related research to measure or to induce decision inertia.

Authors	Decisions	Setting	Operationalization
Akaishi et al. (2014), Gold and Shadlen (2007)	subsequent	Motion discrimination, choice between two or four directions of visual motion, RDM)	In this task the participants are faced with moving dots, while the percentage of moving and resting dots can be varied. The participants are asked to decide between opposite directions.
Achtziger et al. (2012), Grether (1992), Grether (1980)	subsequent	Urn discrimination, between two urns or cages	The participants are faced to priors (two distributions) of two sources. The sources contain a different number of two types of balls, but four balls in total (e.g. one blue vs. two blue). In the first screen of each task the distributions of the two sources are again presented to the participants. In the next step a sample of m balls, between 0 and n balls is drawn from the urn and presented to the participants. Finally, the participants are asked to choose one of the two source as the most likely source of the observed ball distribution. No feedback is given during the experiment. Response-time is measured, and linked to time-consuming process conflict resolution (e.g., Bayesian updating vs. base-rate neglect)
Achtziger et al. (2015), Achtziger and Alós-Ferrer (2013), Charness and Levin (2005)	subsequent	Urn discrimination, between two asymmetric urns	The participants are faced with two subsequent decisions, where they are asked to choose one of two urns as a source of an observed ball distribution (e.g. blue or green balls, or black or white balls). The urns have different distributions and the distributions are known to the participants. They have to guess which of the urns was the source of the observed sample. By drawing one ball (black or white) out of the urns in the first draw, the participants can learn about the state of the urns, and decide in the second draw optimal (considering the information based on Bayesian Theorem) or suboptimal by drawing randomly. The tendency to rely on decision inertia can be measured by comparing error rates in case of conflict and alignment of decision inertia with other processes (e.g., Bayesian updating).

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Table 12 – *Continued from previous page*

Alós-Ferrer et al. (2016), Achtziger and Alós-Ferrer (2013)	subsequent	Urn discrimination, choice between two symmetric urns	The participants were faced to two subsequent decisions, where they had to choose one of two symmetric urns with known distribution, but unknown state. By drawing out one ball (black or white) of the urns, the participants could learn about the state of the urns, and decide in the second draw optimal (considering the information based on Bayesian Theorem) or suboptimal by drawing randomly. The tendency to rely on decision inertia can be measured by comparing error rates in case of conflict and alignment of decision inertia with other processes (e.g. Bayesian updating).
Brody (1965)	sequential (max. 30)	Word discrimination, choice between two words	The participants were asked to guess the most frequently used of one of two words ("plus", or "check"). The experimenter said one of the two words sequentially, after each word the participants could decide to stop and give their guess and their confidence. Earlier answering was rewarded, and the words were distributed (18 to 12, and vice-versa). To investigate the influence of commitment, the participants were divided into groups. The first two groups had to give an initial decision, which was incorrect or correct, while the last group had not to make an initial decision without information. The variance of confidence and round of decision was investigated.
Dutt and Gonzalez (2012), Erev et al. (2010)	sequential (max. 100)	Outcome discrimination, choice between two buttons	Also "e-repeated paradigm"; the participants are instructed to select one of two unlabelled buttons to maximize their outcome. The number of trials are unknown for the participants. A risky alternative (high or low outcome) and a safe alternative (medium outcome) were linked to one of the buttons. Participants were informed only about the result of their decision, and not about the alternative.

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Geller and Pitz (1968), Pitz et al. (1967)	sequential (20)	Bag discrimination, choice between two bags with poker chips	In this experiment, the participants had to choose the most likely of two bags. The two bags contained a fixed number of poker chips (e.g. 100) and were prepared before the experiment. The probability distributions of the chips differed, for instance bag 1 containing 60 red and 40 white chips, and bag 2 vice-versa. The participants were faced with a sample of chips drawn randomly, and with replacement from one of the two bags. Before each single draw, the participants had to predict the color of the next chip, and after the draw they had to report their certainty by turning a wheel to one of three states (bag 1, completely uncertain, bag 2).
Grabitz (1971), Grabitz and Grabitz-Gniech (1972)	sequential (max. 10)	Urn discrimination, choice between different event ratios (ratio of balls in an urn)	Up to 10 draws of a prepared urn with a fixed number but unknown ratio of balls were presented sequentially. The participants, which did not know the true ratio of the urn, had to compare given distribution of balls with regard to their correctness. After each draw, the participants were asked to write down their assumptions about the ball ratio, and the likelihood that the guess is correct. The participants could stop, if they believed that they had identified the correct ratio with a probability of at least 80 %. In an other version, the participants were told that some of the samples were wrong.
Jermias (2001)	subsequent	Usefulness discrimination, choice between two IT-artefacts in a management use case	The participants were asked to choose between two systems or are assigned to one of two groups (System 1 or System 2). The free-choice group was used as a control group compared to the forced-choice group to measure commitment. The commitment was induced by asking the participants to justify their intention for one of the systems. Before and after the decision participants were asked to fill out a questionnaire about perceived usefulness and their resistance to change their beliefs about the first decision
C. R. Peterson and DuCharme (1967)	sequential (max. 100)	Dice discrimination, choice between two different dices	A sample of one hundred dice roles was presented sequentially to the participants. The two dices were six-sided and contained either four white, and two black sides or vice-versa. One of the dice was drawn and used to produce the sample (same dice across the task). The participants had to report their subjective probability that a certain dice was been used.

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Pitz (1969)	sequential (max. 18)	Ball discrimination, choice between two ball colors from a bingo basket	A selection of three red and three blue balls was put into a bingo basket. One unknown ball was removed randomly. In the experiment, the participants were asked to guess the colour of the next draw with replacement of the sample and report their confidence in their judgement (on a scale from 0 to 10).
Polites and Karahanna (2012)		Questionnaire, IS usage intention	Questionnaire with the sub-scales affective-based, behavioural-based, and cognitive-based inertia. Context: "continue using my existing method for collaborating / sharing files with my teammates...", example items: "...because I enjoy doing so." (affective inertia), "...simply because it is what I have always done." (behavioural inertia), and "...even though I know it is not the best way of doing things." (cognitive inertia)
Kozielecki (1966)	sequential (up to 25)	Fertilizer discrimination, choice between different fertilizer	The participants were asked to identify the best of different fertilizer (A, B, C, D, E, H, K). The fertilizer were tested on different plants (rapeseed, hop, or saffron). The participants received sequential reports (plots) from a fake experiment which measured the success of the different fertilizer, and finally had to decide which one performed the best. Deviations from the optimal guesses based on the Bayesian Theorem were computed and compared with the answers from the participants.
Sautua (2017)	subsequent	Ticket discrimination, choice between two lottery tickets	Each of the participants receives one of two lottery tickets, which can be used to take part in a rewarded lottery. The ticket contains a colour, and at the end of the experiment balls are drawn from a bag containing red and blue balls. The participants can switch their lottery ticket, which is rewarded with a small pay-off. Afterwards the lottery is resolved.

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Yu et al. (2010)	subsequent	Choice between two cards	In the first step, the participants are faced with a possible outcome of a lottery (win or loss) for four seconds. Afterwards, the participants have to choose between two cards (left and right) under uncertainty. No information about the probability is given, and without the knowledge of the participants the outcomes are predetermined to have counterbalanced conditions (50 % wins). In each lottery, one of the cards is randomly selected as default and highlighted with a yellow frame. By pressing one of two keys, the participants can decide which of the two cards they would choose.

Finally, however diverse these experimental task might look, they all rely upon a system which allows them to be structured by different characteristics they have in common. The most relevant characteristic is likely that the existing decision inertia measures can be divided into two streams based on underlying research method and the way inertia is measured: observation or questioning. Observed decision inertia measures are calculated based on the behaviour of participants in experimental belief-updating tasks (see e.g. Alós-Ferrer et al. (2016)), while other studies provide questionnaires to measure inter-individual differences in decision inertia (see e.g. Jermias (2001)).

Behavioural measures:

- Decision error (e.g. Charness and Levin (2005); Grabitz (1971); Pitz (1969))
- Response-time (e.g. Alós-Ferrer et al. (2016); Achtziger and Alós-Ferrer (2013))
- Bio-physiological activities (e.g. Jung and Dorner (2017); Akaishi et al. (2014))

Questionnaire (inertia-related):

- Ressistance to change questionnaire (Jermias, 2001)
- Ressistance to change questionnaire with sub-scales affect, behaviour, cognition (Polites & Karahanna, 2012)

As a result, I could identify inertia-related questionnaires (resistance to change), but no explicit inertia questionnaire to measures individual's dispositions towards inertia. As a consequence, I focus on the experimental tasks in the following work. To give a better understanding of the operationalization I now present a short overview of the main design characteristics of these tasks (see Table 13).

One relevant characteristic is the number of *data sources* used to draw the distribution. In most studies, participants face options or data sources, from which to choose. However, other related studies use multiple data sources (Akaishi et al., 2014).

Most of the experimental tasks to measure decision inertia have unknown *discrete states* of the experimental environment. These states are linked to different distributions of the target variable of the participants (e.g. paid ball colour). In most studies, these states are discrete. Other studies differ between simple yes or no questions, linked to different outcomes dependent on their correctness.

In most of the tasks the participants face different *task settings* or framings. For instance they may have to choose one type of specific chips, balls, words or other products (e.g., as with fertilizer (Kozielecki, 1966) or movements (Akaishi et al., 2014)).

Another specific characteristic of the data generation of the decision inertia related experimental tasks is that the events are *symmetrically* distributed. Other studies vary the distribution and built asymmetric settings to test inertia against other cognitive processes such as reinforcement (see e.g., Alós-Ferrer et al. (2016)), while other studies use unknown data generating processes (for the participants) to investigate the behaviour of their participants.

A further characteristic of decision inertia tasks is *stimulus type*. In the studies, participants face a choice set which can be designed in many ways. Furthermore, the feedback (or the information cue) providing the information that can be considered or not in the decision-making process, as relevant to separate inertia from other errors, can have different characteristics. For instance, this feedback can be elicited at the end of the task or during the task (to separate inertia from learning).

Table 13: Design characteristics of related decision inertia tasks identified in literature review.

Data generation	Stimulus	Decision-making
Data sources / distributions: • 1 • 2 • 4 Discrete states: • 1 (yes, no) • 2 (two different states, e.g. colors) Task setting: • chips • balls • words • misc (fertilizer,...) Symmetry: • symmetric • asymmetric • unknown	Type: • choice set • feedback (yes, no, at the end) Sample size: 1 to n Time structure: • subsequent • sequential • independent Draws: • autonomous (free) • required (forced) • mixed, alternating • mixed, prepared • mixed, random Salience: • low (ambiguous or uncertain) to high (certain) • visual, motorial, statistical • framing Valence: • win, loss • physical pain • unknown	Type: • choice: binary, or choose 1 of n • guess: likelihood for source s, or confidence in decision c Incentive: • monetary, linear • monetary, uncertain, lottery • misc (course credits, goodwill) • none Time restriction: • yes • no

The number of decisions measured, *sample size*, or the rounds of the experiment ranges from one pair of subsequent decisions to huge studies with 120 or more draws.

Based on the sample size, the *time structure* of the decisions the participants have to make varies among subsequent decisions, a series decisions, or decisions (made in isolation from one another. In independent-decision scenarios, the participants are normally faced with a sample that has been drawn by a computer and are then asked to make a decision.

The experimental tasks differ also concerning type of *draws* (or selection). For instance, the participant can draw a ball freely from one of two urns. Or he or she is forced to select one specific option in the second round (forced draw). These two types can be mixed in an alternating, prepared, or random order.

Furthermore, the information or the information cue the participants receive can be further differentiated concerning it's *salience*. Salience can be low if the cue is ambiguous or high if it provides "certain" information (e.g., see decision-making under uncertainty vs. certainty). Dependent on the type of the task, the stimulus can further be visual (e.g., point's movement on a screen), a bodily movement, or statistical information. This type of information can be further embedded in a specific framing (e.g. regulatory focus framing).

Related to the salience of the stimulus is the *valence*. this means that the different information (feedback before decision) can be loss vs. win framing. Or a kind of physical pain if the task has a pain-avoidance incentive instead of a monetary incentive (see Suri, Sheppes, Schwartz, and Gross (2013)).

Concerning the *decision type*, decision inertia-related task differ between choices and estimates. In *choice* tasks the participants have to decide between a yes option and a no option, or between multiple urns or strategies (up to n). If they have to *guess*, they are mostly asked to guess the probability of a specific outcome or event. In other tasks, they are asked to rate their individual confidence in their decision.

The pay-offs or *incentives* of the studies also diverge. Some studies have a linear pay-off function, while others studies provide lottery tickets paid after the completion of the study. Others mix these kinds of incentives, or pay their participants with course credits, or participants volunteer.

Finally, another specific characteristic of decision inertia tasks are *time restrictions*. Some studies have only a specific time horizon before participants must answer.

By reviewing the presented decision inertia studies since the 1950s, I have illustrated that there exist various tasks to measure decision inertia. Specifically, judgement and decision-making research provides different sophisticated approaches to measure decision inertia in a neutral setting without co-foundations with other factors. All these task can be describes by different design characteristics (see Table 13), which allow measurement of the influence of different factors on choice repetition, erroneous belief-updating, and control of different individual parameters and inter-individual differences in decision-making.

In addition, there exist various approaches to measure decision-making based on motoral, visual, and cognitive elements of belief-updating tasks in different settings and under different circumstances, while the calculation of decision inertia further differs across the studies. Although these studies provide insight into decision inertia, this subject results in a varied and unacceptably high number of conceptions of decision inertia. There remains a need to provide structure to the discussion and sharpen the understanding and measurement of decision inertia, its underlying mental processes, and its manifestations.

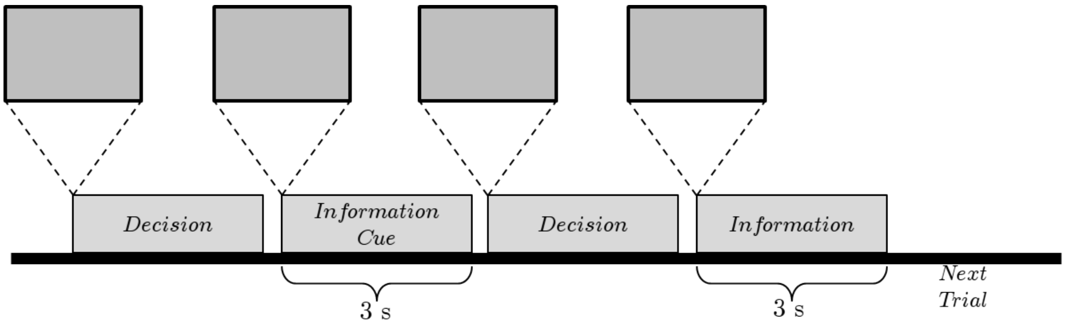


Figure 19: One trial in a belief-updating task containing two choices (2CBU), following the dual-choice paradigm, based on Jung and Dorner (2017), and Alós-Ferrer et al. (2016).

4.2.2 Decision-Inertia in a Dual-Choice Paradigm

This section illustrates that this problem can be solved by generalizing existing tasks to a so-called "dual-choice paradigm" (Jung & Dorner, 2017; Alós-Ferrer et al., 2016), which underlies previous decision inertia studies. In particular, I provide a framework to reproduce decision inertia reliably in the lab, which can be used as a guideline for further decision inertia operationalizations. One further benefit of such a generalization is that this makes existing and future decision inertia studies comparable, facilitating discussion of its influences and drivers. As you have seen, there exist various approaches to measure decision-making based on motoral, visual, and cognitive measures in belief-updating tasks - with such a framework the influence of different factors on decision inertia can be measured directly.

As illustrated in Figure 19, in most decision inertia tasks, the decision-maker is faced with two subsequent (or multiple sequential) decisions. Normally, the first decision is made under uncertainty, and the second or following decisions rely on the first decision and the information provided in response to the first decision (see Figure 19). The reason is that the decision-maker does not know the state of the world and has to make a first decision to gather information. A rational decision-maker would now consider the information and update his beliefs accordingly (e.g. based on the Bayesian Theorem).

To illustrate that in more detail, take for instance the task from Alós-Ferrer et al. (2016) or Pitz (1969). In the first step, participants are faced with two urns, but the state of the environment is unknown to them (in one state, the left urn is better, in the other state, the right one is better). Consequently, they must choose one of the first urns randomly. However, based on the information of the first draw, they can make an optimal or suboptimal subsequent decision.

In this work, I follow suggestions from Alós-Ferrer et al. (2016) that the manifestation of decision inertia is the result of convergent or divergent processes. Decision inertia is one process that potentially conflicts with deliberative processes (e.g., Bayesian updating), and intuitive processes (e.g., reinforcement learning).

Following this rationale, and if only the outcome of a decision is observed, the interaction of the mental processes behind that decision cannot be understood. In particular, in some

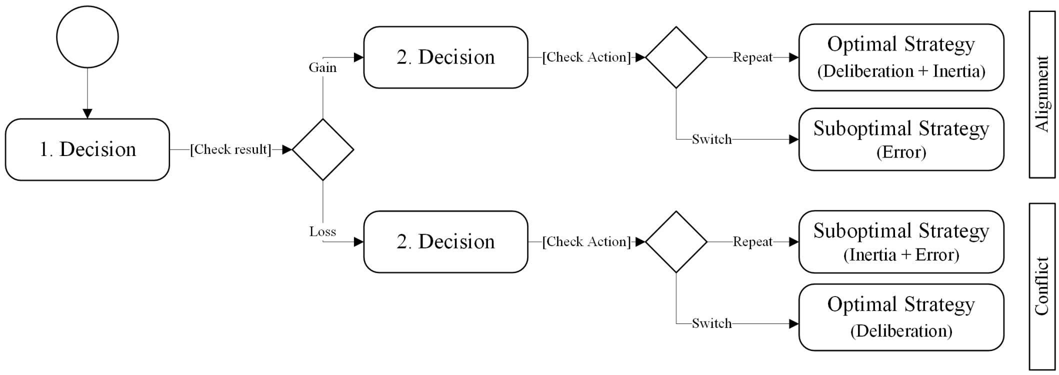


Figure 20: A process framework for the operationalization of decision inertia in a 2CBU, based on (Jung & Dorner, 2017).

situations the repetition of a decision can be rational or strategically useful. Take for instance, a game without consequences of inertia and free information available in the future. On the other hand, there are many situations where this behaviour is suboptimal, or can have at least life threatening consequences (e.g. patient inertia (Suri et al., 2013)). As a consequence, there exist decisions, where the tendency to rely on a previous decision is rational (convergent with other cognitive processes), and where it is not (divergent with cognitive processes).

- **Alignment Situation (Process Convergence):** The decision-maker gets *confirming* information, indicating that his first decision *is probably the optimal decision.* Consequently, decision inertia is *in line* with deliberative processes. If the decision-maker decides to switch to another option, it would be an error.
- **Conflict Situation (Process Divergence):** The decision-maker gets *dis-confirming* information, indicating that his first decision *is probably not the optimal decision.* Consequently, decision inertia is *in conflict* with deliberative processes. If the decision-maker decides to stay, it would be an error.

To find an adequate measure of decision inertia, most studies measure the decision-maker's tendency to under-estimate the new information, or to stick to the previous decision compared to the situation in which it is rational to rely on decision inertia. Such an operationalization is illustrated in Figure 20, and has been in detailed in Section 4.2.1.

Figure 20 illustrates two subsequent decisions. The two stages of the trial allow manipulating the information a decision-maker gets. This is the most popular setup to reproduce the inertia effect reliably in the laboratory. It allows multiple variations to test for other drivers or to control for specific variables (see Table 13). For instance, the decision-maker can be forced to choose a losing or wining option in the first round to manipulate commitment or affect. The decision is based on a single stimulus presentation, thus reducing the cognitive effort to a minimum, and representing a very controlled setting.

4.3 Research Model and Hypothesis Development

Recent behavioural economic and psychological research has suggested that human decision-making anomalies can be explained by dual-processing theory (see Section 2.1). This paradigm suggests that decision inertia can be explained by motivational and cognitive factors in system 1 and its interaction with system 2 processing. In this study, I want to abstract from the specific context of decision inertia, to provide results that can be generalized to other research areas. After investigating decision inertia in a general setting, I want to use these insights to develop counter methods to reduce decision inertia in a specific context (financial decision support, *Part III* of this work, Section 5).

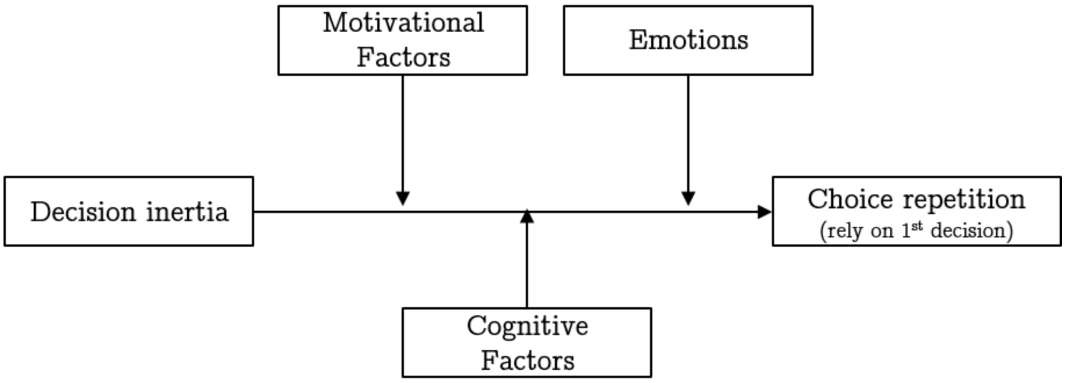


Figure 21: Different possible drivers of decision inertia: Motivational factors, cognitive factors, and emotional factors could explain why people rely on decision inertia in decision-making.

For that purpose, it is necessary to consider especially the motivational, emotional and cognitive drivers of decision inertia. Therefore, the most relevant possible drivers that could be identified in the literature are presented in the following. They are systematically classified in the dual-processing model and their significance for decision inertia is demonstrated.

4.3.1 Consistency-Seeking (H1)

Preference for consistency is a personality trait based on cognitive dissonance theory (Festinger, 1962). It describes the motivation strength of a decision-maker to avoid existing or perceived cognitive inconsistencies like contradictory or conflicting thoughts, states or beliefs (Cialdini et al., 1995). Following this rationale, it is assumed that dissonant cognitions are perceived as highly unpleasant states, and decision-makers use different strategies to reduce them. Decision-makers underestimating their preference for consistency are known for overbidding in wars of attrition and remaining in costly auctions, even if the chances to win are very low (Eyster, 2002). So far, many theories have provided evidence of the aversion of decision-makers to dissonant cognitions (see Rokeach (1960)). The preference for consistency scale measures this sensitivity of decision makers to resolve contradictions by (irrational) behaviour.

In decision inertia research, it is argued that decision makers could commit themselves to the first decision (Pitz, 1969), and hence stick to it because of cognitive dissonance caused by change (Grabitz, 1971; Grabitz & Grabitz-Gniech, 1972). Consequently, decision makers are motivated to avoid dissonance by consistency-seeking, manifesting as decision-inertial behaviour. Other researchers have argued that decision makers do not think through a given issue again, because of their tendency to be consistent, and hence produce decision inertia behaviour (Alós-Ferrer et al., 2016). In contrast, research by Zhang et al. (2014) has found no effect of consistency-seeking towards repeated cheating in a decision task. In their task, participants were faced with two subsequent tasks in which they could easily cheat without being detected. Participants tended to repeat the initial decision across different domains, irrespective of their level of need for consistency. Zhang et al. put forward an alternative explanation, namely that individuals differ in their regulatory focus when pursuing goals (Higgins, 1998). Promotion focus refers to maximizing gains in the long run while prevention focus refers to minimizing losses in the short term. Their results illustrate that prevention focus was indeed linked to tendency to repeat the initial decision, while preference for consistency did not play a significant role (Zhang et al., 2014). However, the experimental setting from Zhang et al. is difficult to compare with previous decision inertia settings. It seems possible that the moral task they used affected decision-makers differently than the neutral decision tasks used in previous studies.

Additional research was devoted to the effects of choice autonomy. It has been argued that if decision inertia is based on the preference to be perceived as consistent, the effect should increase following autonomous decisions, and decrease following forced decisions (Alós-Ferrer et al., 2016). In other words, decision makers will commit themselves more to decisions they choose deliberately but not to decisions that were made under pressure. This expectation is in line with other studies investigating inertia in sequential Bayesian updating tasks (Geller & Pitz, 1968; Brody, 1965), reporting an influence of commitment.

In the study by Brody, participants were asked to make a preliminary decision of one of two choices before receiving information about the nature of these choices (Geller & Pitz, 1968). In the subsequent task, they received information cues from which they could conclude whether this decision was optimal or suboptimal. After each cue, the test participants had to state their confidence in the merit of their decision. The findings show that initial preliminary commitment is related to an increase in initial confidence in a decision compared to no commitment. In the context of unsuccessful decisions it is further related to an overestimation of the success of the option compared to decision makers that committed to a confirming option. Brody concludes that committed decision makers needed more disconfirming information after an unsuccessful decision, compared to decision makers without an initial commitment. This conclusion indicates that even preliminary autonomous decisions under uncertainty could push the decision maker towards decision inertia.

Notably, Zhang et al. (2014) did not observe reliable effects of consistency-seeking on decision inertia. However, their study employed a rather unusual moral decision task that might be responsible for this null effect. I thus opted to test the consistency-seeking hypothesis once again, this time using Alós-Ferrer's more neutral paradigm, which has been shown to elicit decision inertia reliably. Hence, I assume that participants with a high tendency towards consistency will more often show decision inertia.

Hypothesis 1a (H1a). *Decision inertia is associated with an individual's preference for consistency.*

Hypothesis 1b (H1b). *Decision inertia is associated with decision autonomy, that is, free initial decisions increase, forced initial decisions decrease decision inertia.*

4.3.2 Indecisiveness (H2)

Closely related to this concern is another motivational factor, namely indecisiveness. This construct describes the inability to make decisions in a timely manner across situations and domains (Frost & Shows, 1993). It has two components: first threat-oriented cognition and negative affect in response to decisions, and second one that manifests as avoidant preferences and difficulties in response to decisions (Spunt et al., 2009). Compared to indecision, that is, an individuals' inability to find a solution that fits his or her preferences best, indecisiveness targets individuals' dispositions such that no decision is taken and that they experience difficulties in reaching a decision (Germeijs & De Boeck, 2002). Hence, I expect that individuals who experience more indecisiveness than others will be more likely to repeat a previous decision regardless of the consequences.

Evidence for this hypothesis is provided by Sautua (2017) who reported an influence of indecisiveness on decision-inertial behaviour. Similarly, J. W. Payne, Bettman, and Johnson (1988) reported the role of indecisiveness and decision time in a risk condition. They observed an increased response time for indecisive individuals compared to decisive individuals. This finding is in line with existing decision inertia research from Alós-Ferrer who reported a positive correlation between decision inertia and response times (Alós-Ferrer et al., 2016; Achtziger & Alós-Ferrer, 2013). Notably, this effect exists only in risk conditions, in no-risk conditions decisive individuals and indecisive individuals did not differ (J. W. Payne et al., 1988), an observation comparable to the findings from Charness and Levin who found that risk-reduction (only paying the second decision in a subsequent task) also reduced the inertia rate (Charness & Levin, 2005). Payne also observed that highly indecisive participants tend to favour less exhaustive decision strategies. Taken together, these findings suggest that decision inertia could partly result from the motivational trait of indecisiveness.

Summarizing these concerns, I argue that decision inertia could be caused by indecisiveness in addition to consistency-seeking as an underlying motivation. Thus, I expect that individuals will exhibit less decision inertia if I offered a choice set with a decision avoidance option as compared to the standard choice set in which they are forced to decide. In addition, I expect that individuals hesitant to make decisions as measured by the indecisiveness scale (Frost & Shows, 1993) are more likely to rely on decision inertia.

Hypothesis 2a (H2a). *Decision inertia is positively associated with an individual's indecisiveness (as measured by the indecisiveness scale (Frost & Shows, 1993).*

Hypothesis 2b (H2b). *A decision avoidance option will disentangle the repetition of a choice from rejecting a decision and hence reduce decision inertia, compared to decisions with no such option.*

4.3.3 Emotions and Arousal (H3)

Deliberative decision-making relies on the interplay of sensory and emotional information, and memories of previous decisions and outcomes (Haber, 2011). A driver of biased decision-making, counteracting these deliberative processes, is arousal. Because, intuitive processes are processed with substantially less cognitive effort, combined with a low threshold for processing information (Strack & Deutsch, 2004), arousal influences individuals tendency to rely on these processes (Sanbonmatsu & Kardes, 1988). In particular, in decision-making under risk, recent research illustrates the negative influence of high levels of arousal on subjective evaluations (Dhar & Gorlin, 2013). Regarding decision inertia, there is evidence that arousal could be a possible reason for individuals to rely on decision inertia.

Initial evidence, pointing to the influence of affective arousal on decision inertia can be found in Charness and Levin (2005). In a sequential belief-updating task, the decision inertia effect can be reliably reproduced (Alós-Ferrer et al., 2016). However, they also reported that, if the first decision is not rewarded, the decision inertia effect is reduced. Hence, the (affective) response to the first decision seems to be a relevant driver of decision inertia. More evidence for this hypothesis comes from (Yu et al., 2010). In a study, investigating the neural basis of repetition behaviour, reliance on a default could be linked to brain areas responsible for anticipating risk and risk-attitude. Hence, inter-individual differences in affective responses to the first decision in the ventral stratum, along with the linked bio-physiological responses, could be a possible explanation for occurrences of decision inertia (Yu et al., 2010).

If decision inertia is a cognitive process potentially conflicting with deliberative processes like Bayesian updating, we expect that this conflict also manifests physiologically. Hence, because the tendency to resist decision inertia and to rely on deliberative thinking requires more effort than relying on intuitive processing, this tendency should increase an individual's cognitive arousal. This assumption supports existing approaches to measure decision-inertia physiologically, as in the work of (Alós-Ferrer et al., 2016), who propose decision-time as a further indicator for the conflicting processes and the tendency to rely on decision inertia.

Hypothesis 3 (H3). *An increase in arousal is associated with an increase in deliberative thinking, and hence with decreased error rates.*

4.3.4 Action Orientation (H4)

Next, I turn to the question of the degree to which decision inertia is driven by the results of previous decisions. The theory of action control (Kuhl, 1994b, 1981) suggests that people differ in disposition as to how they process negative or positive events. In particular, the theory of action control suggests that the manner in which negative events are processed is moderated by the action orientation of a decision maker. Action orientation is a personality dimension and can be measured using the action orientation scale by Kuhl.

Research suggests that highly action-orientated decision makers go easily about negative events, are more overconfident in their ability to influence events, and are more motivated to take action (De Lange & Van Knippenberg, 2009; Jostmann, Koole, Van Der Wulp, & Fockenberg, 2005; Kuhl, 1994b). For instance, Raab and Johnson have observed that action-oriented players made faster and riskier decisions than did less action-oriented decision makers (Raab & Johnson, 2004). On the other hand, low action-oriented (so-called state-oriented) decision makers are barely able to regulate their emotions and to accommodate negative experiences. It is important to note that action orientation may not only help decision makers to overcome negative consequences and maintain intentions but that it is also linked to the tendency to make a decision too quickly and without considering possible negative consequences in sufficient detail. These features of action orientation have been replicated in the context of irrational choice negation and inaction inertia (Van Putten, Zeelenberg, & Van Dijk, 2009). Moreover, Kazén et al. have reported that state-oriented participants who have difficulties overcoming negative events perform better in error detection than do action-oriented participants after experiencing a negative affect (Kuhl, 1994b, 1994a, 1981).

Following these arguments, I assume that action orientation could partly explain why decision makers rely on decision inertia. To illustrate this, let us first assume that the first of two subsequent decisions was suboptimal. State-oriented decision makers will tend to rethink their next decision and not make it regardless of the consequences, because they cannot easily ignore the negative affect of the loss. However, action-oriented decision makers will not attach any particular importance to the loss and will make their decision regardless of this loss. Therefore, they will also tend to repeat a suboptimal decision that resulted in a loss, and thus show more decision inertia.

This consideration leads us to our next hypothesis. I expect action-oriented or disengaged decision makers to be more prone to exhibiting decision inertia. Specifically, because they will be less influenced by the negative result of the first decision, they will more likely rely on the suboptimal choice again, as contrasted compared to state-oriented decision makers who perceive the loss information more severely (van Putten, Zeelenberg, & Van Dijk, 2013; Van Putten et al., 2009).

Hypothesis 4 (H4). *Decision inertia after a loss is positively associated with an individual's action-orientation.*

4.3.5 Bayesian Updating and Conservatism (H5)

The foregoing discussion has focused on motivational variables that have so far been investigated as determinants of decision inertia almost exclusively. In the current work, I extend the psychological perspective by including potential cognitive variables as well. I propose that decision inertia varies with cognitive factors. Our first assumption relates to the processing of uncertain information and the process of updating probabilities of hypotheses based on a sample of observations. Experimental studies have provided ample evidence of conservatism in the intuitive probability estimates of humans, caused by imperfect Bayesian updating (Phillips & Edwards, 1966). Conservatism means that newly acquired sampling information is considered to an insufficient degree as compared to the normative standard of the Bayesian' theorem. Rather, people tend to rely on base-rates determined on a priori grounds more than they should according to Bayes' Theorem.

By comparing subjective with objective probabilities, Little and Lintz reported constant differences at the subject level that could partly explain the deviations of future subjective probabilities from correct Bayesian probabilities (Little & Lintz, 1965). Following this rationale, this conservatism bias may lead to seemingly irrational behaviour – in our case, to the insufficient updating of a prior belief and hence, to a repetition of a decision that has become less favourable according to the new and incoming information. Thus, the well-documented Bayesian conservatism might explain decision inertia without the need to invoke motivational explanations.

Hypothesis 5 (H5). *Decision inertia is associated with suboptimal Bayesian updating (i.e., conservatism, cf. Phillips and Edwards (1966)): The more conservatism in Bayesian updating, the stronger the decision inertia effect.*

4.3.6 Evidence Threshold (H6)

Furthermore, I propose that a further cognitive factor refers to the accumulation of evidence against a currently held hypothesis vis-á-vis the individual *evidence threshold* of a person – that is, how much evidence is required to convince a person to switch to an alternative hypothesis or, in other words, to reject a currently held hypothesis.

A similar concept was proposed in early Bayesian-updating studies (Kozielecki, 1966). Kozielecki proposed that decision makers vary in that they can require different levels of evidence to accept a hypothesis as true. He reported that participants did not adjust their level of confidence after disconfirming information, until a specific level of evidence was accumulated. Also, Hausmann and Läge (2008) have showen that an individually assessed evidence threshold could predict subsequent information search and stop behaviour better than various decision heuristics proposed in the literature (Hausmann & Läge, 2008). Similarly, Söllner and Bröder (2016) have demonstrated that participants varied considerably in their evidence thresholds, but the thresholds were also sensitive to extrinsic factors such as acquisition costs (Söllner &

Bröder, 2016).

Whereas our first cognitive explanation focuses on the *ability* to properly update probabilistic information, the second one emphasizes *individual differences* in the desired level of confidence (e.g., the probability or evidence against, which a currently held hypothesis can be abandoned in favour of a hypothesis)

Hypothesis 6 (H6). *Decision inertia is associated with individual differences in evidence thresholds: The higher the threshold, the stronger the inertia effect.*

4.3.7 Faith in Intuition (H7)

Furthermore, I assume that individuals' tendency to rely on decision inertia is associated with the tendency to use heuristic processing and cognitive shortcuts. For instance, biased decisions have been associated with lower capacity for cognitive reflection (Hoppe & Kusterer, 2011), as measured by the cognitive-reflection test (Frederick, 2005). Alós-Ferrer and Hügelschäfer have shown that high scores in the cognitive-reflection test are linked to overweighting of the sample information (Alós-Ferrer & Hügelschäfer, 2012). In a subsequent study, Alós-Ferrer and Hügelschäfer compared the influence of differences in the intuitive-analytic cognitive styles of decision-makers on errors in probability judgments (Alós-Ferrer & Hügelschäfer, 2016). They found evidence that the tendency to rely on heuristic decision-making and suboptimal probability processing. Following this rationale, I assume the following:

Hypothesis 7 (H7). *Faith in intuition is positively associated with decision inertia*

4.3.8 Framing (H8)

Relying on regulatory focus and framing literature, I assume a relationship between a specific regulatory focus orientation and decision inertia. In particular, promotion-focused individuals are more likely to behave more riskily in memory classification tasks (Higgins, 1997). This behaviour is in line with the findings of Liberman et al., who showed that promotion-focused individuals are more likely to exchange a resumed task for a different task (Liberman, Idson, Camacho, & Higgins, 1999). They showed the same for changing an endowed object. Hence, promotion-focused individuals are open to change and tend to revise previous decisions even if the new situation does not explicitly represent a gain. This proclivity makes promotion-focused individuals hold less to previous decisions, even if they had positive outcomes. This is in accordance with Friedman and Foerster, who showed that promotion-oriented individuals are more creative and tend to use less conservative strategies in order to come up with new ideas Friedman (2001, p.102). In a subsequent study, they could show a relationship between promotion-focus and less accurate but faster task performance (Förster, Grant, Idson, & Higgins, 2001), which should increase their error rates when Bayesian updating is in line with decision inertia. On the other hand, considering prevention focus, Friedman and Förster found that prevention focus cues, for example cues that induce a prevention focus state, lead to

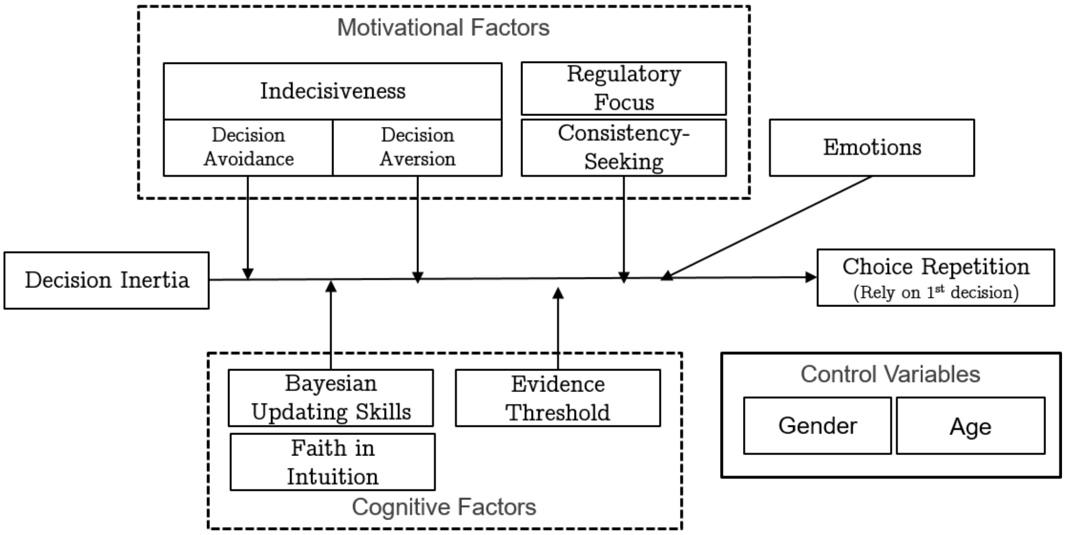


Figure 22: Final research model, with the most relevant potential drivers of decision inertia, separated into motivational, cognitive and emotional factors.

more risk-averse, less creative and hence a more perseverate processing procedure (Friedman & Förster, 2001). Specifically, they had participants think of as many ways of use for a brick that they can think of. They found that prevention-focused individuals used many exemplars that they had already used in a previous task or associated material and hence came up with less innovative, but more conservative ideas. Liberman et al. showed that prevention-focused individuals tend to resume with an interrupted task (Liberman et al., 1999), showing a tendency to adhere previous decisions. This finding accords with those of Zhang et al. (2014), who showed that a prevention focus leads to a repetition of even immoral previous behaviour.

As a consequence, I assume that promotion-focused individuals will behave in more exploratory and risky ways, while prevention-focused individuals behave more conservatively and repeat a decision. Therefore, I argue that prevention-focused decision-makers should show more decision inertia (loss vs. non-loss framing), and promotion-focused decision-makers respectively less decision inertia (gain vs. non-gain framing).

Hypothesis 8 (H8). *A situational prevention focus (loss vs. non-loss) compared to a promotion focus (gain vs. non-gain) is positively associated with decision inertia*

4.4 Investigating Motivational and Physiological Drivers of Decision Inertia

The main purpose of this experiment was to examine motivational and emotional drivers of inertia in decision-making. I assumed that motivational aspects and emotions could explain why decision-maker rely on decision inertia. As the subsequent studies of this part, this work builds upon a multiple-process perspective of decision inertia, as proposed by Alós-Ferrer et al. (2016) and Alós-Ferrer and Strack (2014). Hence, I consider decision-making as the result of interacting processes that can converge or diverge (see Section 2.1). Based on this perspective, Alós-Ferrer and colleagues suggest that decision inertia is caused by automatized, unconscious, and effortless processes that diverge from rational, slow, resource-consuming deliberations Alós-Ferrer et al. (2016). This understanding of decision inertia, that I adopt here, suggests that decision inertia can be observed when intuitive and deliberative decision processes are in divergence, resulting in more suboptimal outcomes.

4.4.1 Method

The dependent variable of this investigation is decision inertia, that is, the decision-makers' tendency to repeat the previous decision regardless of the consequences, even if it is clearly inferior to other options (Sautua, 2017; Alós-Ferrer et al., 2016). In an experimental task, decision inertia means that decision-makers will repeat their previous decision.

To test the first three hypotheses (H1a, H1b, H2a, H2b, and H3), I made use of the dual choice paradigm based on experimental tasks that have previously been used to induce decision inertia (Alós-Ferrer et al., 2016; Pitz, 1969).

Fur this purpose, I implemented the urn game task from Alós-Ferrer et al. (2016); Charness and Levin (2005) two choice options. The game includes two equally likely states of the world ("up" and "down") and two lotteries (left and right). The lotteries consist of two urns, each of which contains six black or white balls. In the up state, the left urn contains four black balls and the right urn contains two black balls. In the down state, the distribution of black balls is reversed: The left urn contains two black balls, the right urn four.

One round of the game consists of two consecutive urn draws such that drawing a black ball results in a reward. The state of the world remains constant throughout one round (e.g., two consecutive draws). The participants can choose freely whether to draw from the left or the right urn but they have no information about the state of the world prior to the first draw. After the first draw, they can infer the most likely state of the world (hence, the pay-off-maximizing urn choice for the final draw) based on the colour of the drawn ball. If participants are fully rational Bayesian updaters, it is expected for them to make pay-off-maximizing choices by always choosing the urn with the higher probability of containing four black balls.

Following the dual-choice paradigm, I would expect participants who exhibit decision inertia to stay with their first choice. If they chose the right urn for the first draw, they will chose

Table 14: Implemented lotteries of the urn game, based on (Alós-Ferrer et al., 2016; Pitz, 1969).

State	Left Urn	Right Urn
up (p=.5)	● ● ● ● ○ ○	● ● ○ ○ ○ ○
down (p=.5)	● ● ○ ○ ○ ○	● ● ● ● ○ ○

the right urn for the second draw – regardless of the consequences of their first decision. For example, let us assume that the participant chooses the right urn in the first draw. If the result is a white ball, it is more likely that the state of the world is *up*. To maximize their chances of drawing a black ball in the second draw, the participant ought to choose the left urn for their second draw. Staying with the first (i.e., inertia-driven) choice would be suboptimal.

Conversely, if the participant chose the right urn in the first draw and came up with a black ball, it is more likely that the state of the world is *down*. The participant ought to choose the right urn again for their second draw. Optimal choice and inertia-driven choice would be identical in this case (choose right urn again).

I expect that if decision inertia is present, I will observe more suboptimal decisions when Bayesian updating and decision inertia-driven choices diverge (e.g. in the case of drawing a losing ball first). In this situation, decision inertia would predict to repeat drawing from that urn, while correct Bayesian updating suggests switching urns. These two processes are in divergence and result in two different behavioural outcomes. However, when the first ball is a win, both processes converge and predict to repeat the urn. Following this rationale, I measure the occurrence of decision inertia by comparing the rate of suboptimal decisions in the sense of Bernoulli rationality, and response times between all situations where Bayesian updating and decision inertia are in convergence or in divergence (Jung & Dorner, 2017; Alós-Ferrer et al., 2016).

To test whether decision inertia is driven by indecisiveness between the two urns, I implemented a third option. Every second pair of draw decision participants is faced with an avoidance option. This option results in a small but fixed return. I assume that this option would give indecisive individuals the possibility to choose an option without deciding (H2ab).

4.4.2 Participants

40 adult participants (27 male, 13 female, age range=18-29, M=22.4, SD=3.06) took part in the experiment at Karlsruhe Decision and Design Lab. They received a participation fee of 2.50 Euro and a performance-based payment of 0.10 Euro for each drawn black ball. Mean pay-off was 6.48 Euro (SD=0.47). If they decided to press the avoidance option, they got a small fixed return (0.01 Euro). The experiment took approximately 30 minutes.

Figure 23: Procedure of the experimental investigation of Study 1.

4.4.3 Physiological Measures

In this study I used Electrocardiography (ECG), to measure the electrical activity of the heart. I measured the heart rate in beats per minute, which is a common proxy for the participants current level of arousal (Mauss & Robinson, 2009; Berntson & Cacioppo, 2007). Following H3, I assumed that decision inertia and arousal are associated with increased cognitive effort, resulting in increased heart rate variability measured by the ECG. In particularly, I focus on the arousal of each individual decision-maker in each phase of the experiment (e.g, first draw, first result, second draw, and second result). Every decision-maker's heart rate was measured relative to basic arousal level as assessed in a calibration phase before the experiment (θHR).

4.4.4 Procedure

In a first step, the decision task, instructions and questionnaires were chosen in line with (Alós-Ferrer et al., 2016) and Achtziger and Alós-Ferrer (2013). In this design, participants are faced with two choice situations or treatments. Based on the result of the first choice, in the second choice the decision to rely on the previous option can be optimal (correct Bayesian updating), or it can be suboptimal (no correct Bayesian updating). I measure decision inertia as the tendency to rely on the first of two subsequent choices, regardless of the outcome of the first one by comparing the rates of suboptimal decisions in case of divergence and convergence of decision inertia and Bayesian updating. To measure the influence of indecisiveness, I added an avoidance option labelled "Decline" in every second two-draws round. Because I wanted to reduce confounding effects, I varied the choice sets (standard vs. with avoidance option) alternately.

Overall, I organized the experiment based on the general experimental framework for conducting IS experiments with Brownie (Jung, Adam, Dorner, & Hariharan, 2017). Consequently, the experiment consisted of five main steps: In the first step, the sensors were attached to the participants. The sensors of female participants were configured and attached by female research assistants, and for male participants vice-versa. Afterwards, the participants received instructions on the experiment and their task. Only after they had successfully completed a comprehension test could participants proceed to the actual experiment. In the third step, participants played the two-draw urn game 40 times (80 draws) with the standard choice set and the avoidance choice set alternately. In the last step, they were asked to complete questionnaires on demographics and personality-related characteristics: indecisiveness (see Spunt et al. (2009), appendix Table 21), the short scale of preference for consistency (see Collani and

Blank (2013), appendix Table 23), and action- and state-orientation (see Kuhl (1994b), appendix Table 25).

4.4.5 Results

I computed the individual rates of suboptimal decisions in the two choice situations. Hence, I compared the participant's tendency to make an optimal decision under divergent conditions (divergence between Bayesian updating and decision inertia) vs. convergent conditions (convergence between Bayesian updating and decision inertia). An optimal decision is a decision in the sense of the Bayesian theorem. If Bayesian updating predicts the repetition of a decision, decision inertia is in line with the optimal decision. However, it results in suboptimal decisions if it would be optimal to switch according to Bayes' theorem. A major explanation of suboptimal decisions in divergent conditions is that participants rely on decision inertia, while an explanation of suboptimal decisions in convergent situations might be that the participants simply make careless errors in their behavioural response (e.g., clicking the wrong choice).

The mean rates of suboptimal decisions in the two choice situations in case of divergence and convergence between inertia and correct Bayesian updating were 32.8 % (SD=29.2) and 6.5 % (SD=10.4), respectively. Hence, decision makers decided much more frequently in a suboptimal way if decision inertia and Bayesian updating prescribed opposite choices. Because the error rates are not normally distributed, I used a non-parametric test for differences in medians. A two-tailed Wilcoxon signed rank test indicated that mean error rates in case of divergence were significantly higher than in case of convergence ($n = 40, Z = 4.7883, p \leq .001, r = .76$). Previous studies reported similar error rates (Alós-Ferrer et al., 2016). Hence, our results suggest that I were able to replicate the decision inertia effect reliably in our setting and that the effect size is similar to that of previous studies (e.g. Alós-Ferrer et al. (2016)).

Because I assumed that decision inertia could be driven by decision avoidance (H2b), I added a third button that returned a small but fixed pay-off of 0.01 Euro (see above) to provide an adequate possibility for indecisive individuals to choose an option without the need to process the information or to actively decide upon one of the two urns. To investigate this assumption, I checked for significance differences between the two different choice sets. In a first step, I split the data into two choice sets with and without the avoidance option, and then I checked whether the decision inertia effect persisted in both sets. A two-tailed Wilcoxon signed rank test indicated that the differences in mean error rates were significant for both choice sets (standard set: $Z = 4.4836, p \leq .001, r = .72$, set with avoidance option: $Z = 4.4226, p \leq .001, r = .71$), but mean error rates between the two choice sets did not significantly differ (convergence: $Z = 0.53931, p \geq .05, r = .08$; divergence: $Z = 1.3462, p \geq .05, r = .21$). Figure 24 illustrates these relationships.

However, the avoidance option was rarely chosen: Only 9 times did participants decide to choose the avoidance option instead of one of the two urns in the whole experiment (n=3, min=2, max=4).

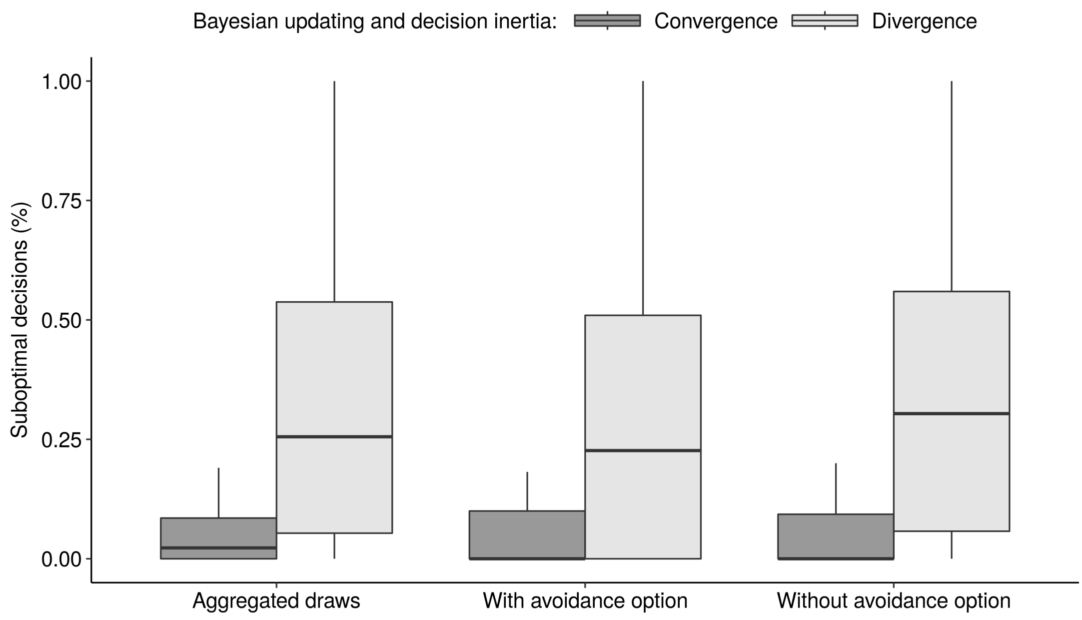


Figure 24: Suboptimal behaviour distributions in decisions with and without an avoidance option.

Other studies suggest that the conflict of decision inertia and deliberation manifests additionally as increased response times (Alós-Ferrer et al., 2016). Mean response times in case of conflict were 1562 ms (median=1539 ms, SD=402 ms) and in case of alignment 1473 ms (median=1448 ms, SD=423 ms). A two-tailed Wilcoxon signed rank test indicated that there was significant difference ($n = 42, Z = 1.77, p \leq .1, r = .3$).

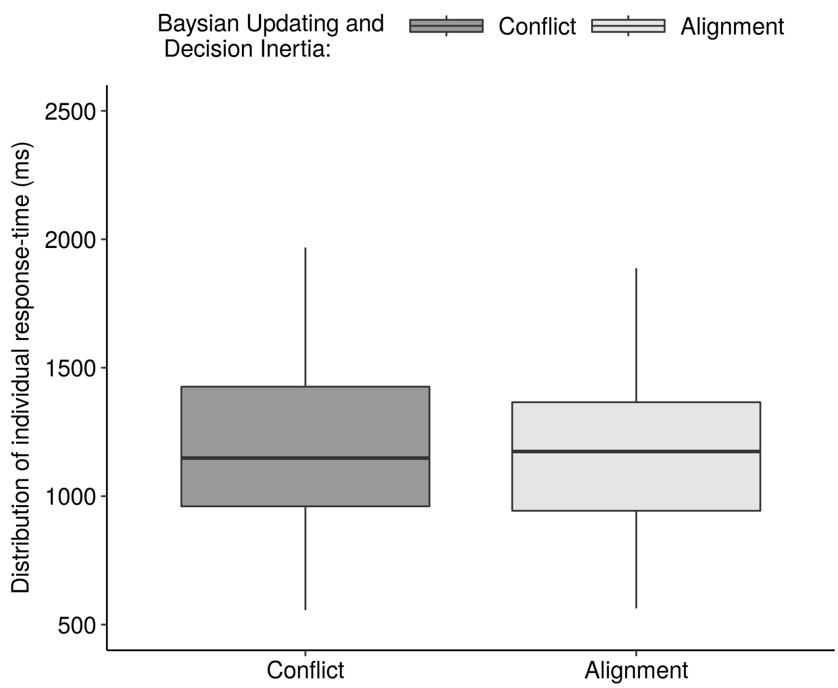
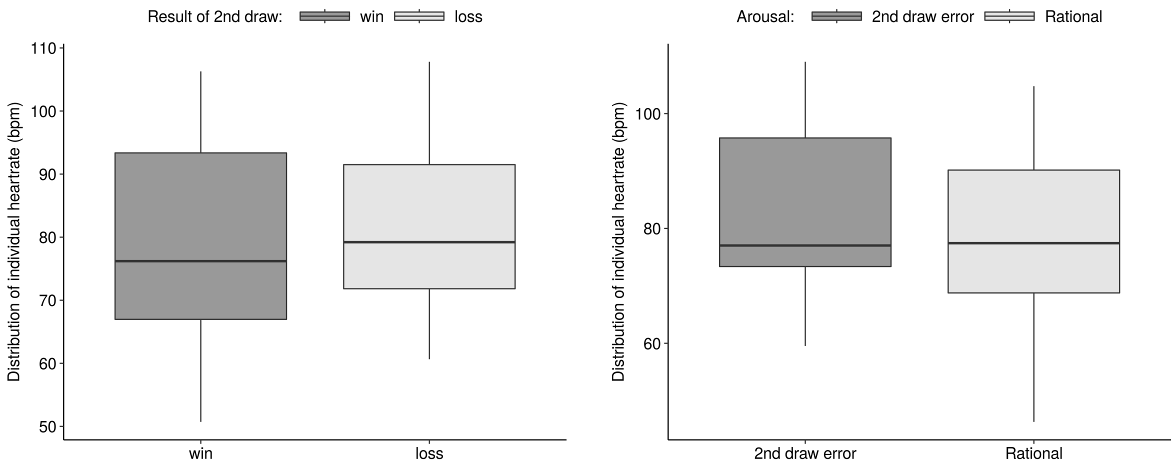


Figure 25: Comparison of the distribution of individual response-times in case of conflict (black) and alignment (grey)

As an indicator of arousal, I measured individuals' heart rates before the experiment, and during decision-making. Heart rates were derived from the ECG data determined with bio plux hubs. To compare heart rate changes across participants I computed an additional heart rate value per participant normalized by the baseline heart rate from the initial rest period.



(a) Arousal in win vs. loss condition **(b)** Arousal after optimal vs. suboptimal decision

Figure 26: Comparison of the distribution of arousal after a positive result (black) and negative result (grey), or after overcoming decision inertia compared to relying on decision inertia.

At first, I computed the mean arousal level during decision-making in case of aligned and conflicting processes. Mean heart rates in case of conflict were 72.6 bpm (median=75.5 bpm, SD=25.6 bpm) and in case of alignment 72.0 bpm (median=76.2 bpm, SD=26.6 bpm). A two-tailed Wilcoxon signed rank test indicated that there was no significant difference ($n = 42, Z = 0.36, p \geq .05, r = .05$).

Secondly, I compared the mean arousal level of the participants after decision-making. A two-tailed Wilcoxon signed rank test indicated that there was no significant difference of mean heart rates ($n = 42, Z = 1.6, p \geq .05, r = .25$) in case of relying on a suboptimal decision (mean=76.0 bpm , median=76.4 bpm, SD=25.3 bpm) and in case of correct Bayesian updating (mean=74.0 bpm, median=76.4 bpm, SD=25.5 bpm). However, I found significant ($n = 42, Z = 2.49, p \leq .05, r = .4$) differences in case of a positive result (mean=74.2 bpm , median=75.7 bpm, SD=23.7 bpm) and in case of a negative result (mean=75.9 bpm, median=77.8 bpm, SD=24.0 bpm).

Furthermore, I found a decreasing heart rate across the experiment (see Figure 27), in line with recent findings in the literature and linked to a habituation effect of participants towards the task and the experimental situation (Wilson, 1992).

Regarding the error distributions at an individual level, I found considerable heterogeneity across individuals. Similar results have been reported by Alós-Ferrer et al. (2016); Charness and Levin (2005), indicating that our results matched those of other researchers also at the individual level. Figure 28 illustrates the frequency of individual error rates across the participants.

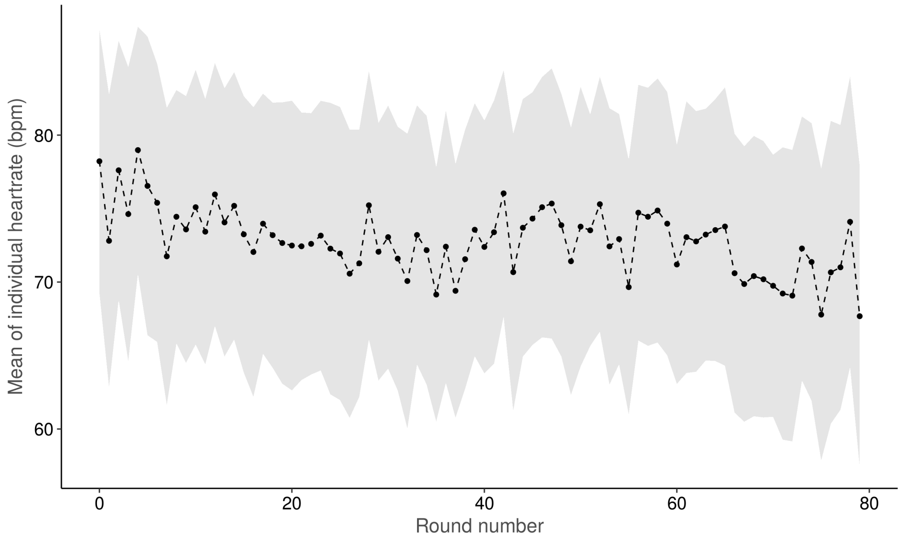


Figure 27: Deceasing arousal level across the experimental treatment.

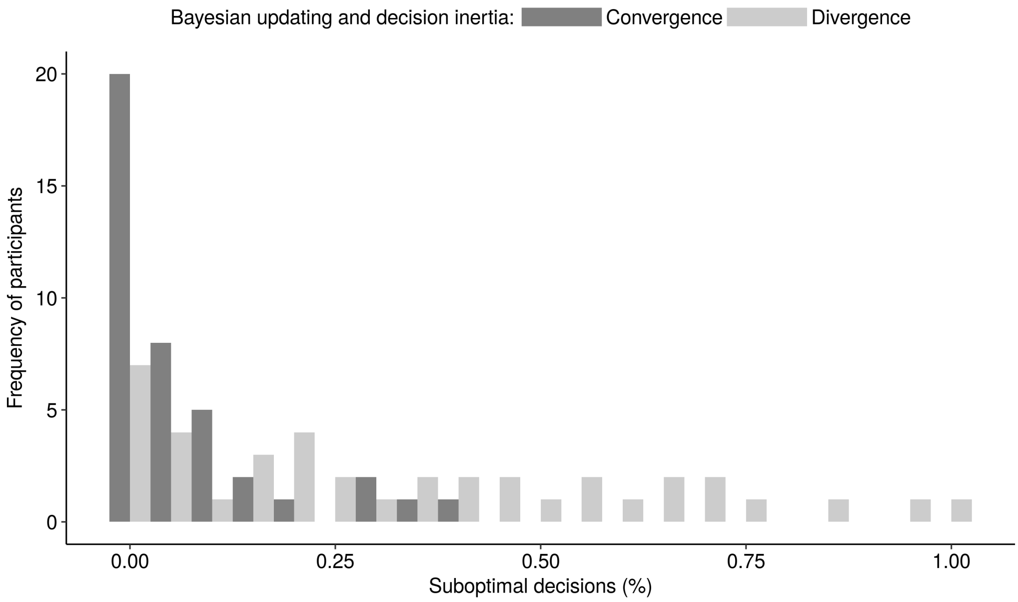


Figure 28: Frequency of suboptimal behaviour in case of convergence or divergence with decision inertia.

To investigate possible antecedents of decision inertia, I measured different personality traits. Following the urn game, all participants had to complete a web-based questionnaire. With the exception of the preference for consistency score (mean=3.47, SD=0.82, α=0.62, each item measured on a 5-point Likert scale), the internal consistency of our independent personality-related variables indecisiveness (mean=2.83, SD=0.72, α=0.85, also measured using 5-point Likert-scales per item), and decision-related action-orientation (mean=0.53, SD=0.25, α=0.76, binary scale per item) was overall around 0.8, indicating sufficient internal consistency of the construct measures.

I followed previous studies (Alós-Ferrer et al., 2016; Charness & Levin, 2005) and conducted a random effect regression on suboptimal (e.g., non-Bayesian) decisions (binary variable, 1=True) to take the individual observations into account. I considered each participant as a random effect and all other factors as fixed effects. To compare situations where decision inertia diverged versus converged with Bayesian updating, I added a dummy variable indicating divergence (binary variable, 1=True). Note that this variable allows one to distinguish whether the predictors considered affect suboptimal behaviour in general (no interaction with divergence dummy) or whether they affect the occurrence of decision inertia selectively (interaction with divergence). This is a common procedure to measure the influence of factors on decision inertia (see e.g. Alós-Ferrer et al. (2016); Charness and Levin (2005)). All variables were z-standardized to obtain standardized beta regression coefficients.

Table 15: Random-effects probit regression on suboptimal behaviour (1=suboptimal).

Variable	Beta (SE)	P
(Intercept)	-1.67	< 0.001 ***
Action orientation	-0.28	0.11
Divergence (1=True)	1.37	< 0.001 ***
Preference for Consistency	-0.19	0.23
Indecisiveness	-0.02	0.89
Avoidance Option (1=True)	0.06	0.69
Trial Number	-0.07	0.10 .
Gender (1=Male)	-0.43	0.15
Divergence x Action orientation	0.28	< 0.01 **
Divergence x Preference for Consistency	0.08	0.42
Divergence x Indecisiveness	0.10	0.32
Divergence x Avoidance Option	-0.13	0.50

Number of obs: 1560; **random effect:** participant id, **participants:** 40; **Tjur's D** = .308, **Signif. codes:** 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Considering the non-interaction effects, there is a positive effect of divergence ($p < 0.001$) as expected. This indicates that divergence of cognitive processes leads to a generally increased risk-ratio to make a suboptimal decision.

On the other hand, if I split suboptimal behaviours into choice repetition when switching is better (decision inertia; divergence = True) and switching when repetition would be more optimal (error; divergence = False) by considering the interaction of divergence with other predictors, I find a significant influence of action orientation. Because action orientation is only significant as an interaction effect with the divergence indicator, this finding suggests that action orientation boosts decision inertia selectively, not suboptimal second-draw decisions in general.

4.4.6 Discussion

The results do not support the notion that decision inertia is driven by motivational influences such as commitment or consistency-seeking. In this setting, the regression (see Table 15) showed no significant influence of preference for consistency and no significant interaction effect between consistency-seeking and divergence. This finding suggests that the tendency to repeat a decision might emerge for other reasons. At first glance, this result is align with findings such as those of Zhang et al. (2014), who reported no significant influence of preference for consistency. Nevertheless, recent research also shows that decision inertia is a subtle process (Alós-Ferrer et al., 2016). It cannot be ruled out that the avoidance option available in every second choice set of our setting could have diminished the participants' need to feel consistent. Conversely, the "free-choice vs. forced-choice" setting of Alós-Ferrer et al. (2016) could have pushed participants to be consistent with their initial decisions. I test these possibilities in the next study. Another reason for these inconsistent findings might be, that the results revealed only a very low internal consistency for the preference for consistency score (α = 0.61) in the sample.

Additionally, I checked for possible influences of individual differences in indecisiveness (H2a) or decision avoidance (H2b). In both cases I found no significant influence, in particular no influence of the avoidance option on error rates, and no influence of indecisiveness on a tendency to avoid a decision or repeat a previous decision. This lack of influence suggests that indecisiveness as a motivation to avoid decisions or negative affect when making decisions (Spunt et al., 2009), is probably irrelevant with respect to decision inertia, at least in the decision paradigm used here.

However, the significant interaction between action orientation and divergence indicates that a high score in action orientation is linked to increased risk-ratio for decision inertia. Action-oriented decision makers go easily about negative events, and hence more often show decision inertia.

Finally, the effect of trial number tended to be negative (albeit not significantly so, p = 0.1) suggesting that participants committed fewer errors in second draws the longer the experiment took. This trend might be due to learning effects, that is, gaining experience with the task might result in better performance overall. These findings agree with those of other comparable studies that also reported fewer second draw errors in later trials (Alós-Ferrer et al., 2016; Charness & Levin, 2005). This agreement is interesting, because it suggests that decision inertia could be reduced by extended training in Bayesian updating.

4.5 Investigating Cognitive Drivers of Decision Inertia

The aim of this study was to propose and investigate a possible explanation of the mixed motivational findings concerning decision inertia. I hypothesized that inter-individual differences in cognitive reflection, and inabilities to correctly process Bayesian information could further be relevant drivers of the inertia phenomenon. The mixed findings in previous studies may be explained by inter-individual differences in cognition.

4.5.1 Method

In this setting, I relied again on the setting of the first task of first experiment (see the previous section). To compare situational regulatory focus, I had to implement a second variant of this experimental task. In this variant, I faced the participants with two framed situations that were equivalent with respect to probabilities and objective outcomes (see Otto, Markman, Gureckis, & Love, 2010; Shah, Higgins, & Friedman, 1998). Specifically, the framing of the urn game was changed to a task oriented around loss framing versus win framing, executed similarly to previous studies (Alós-Ferrer et al., 2017). In the loss frame condition, participants received an initial endowment of EUR 0.20 for each two-draw decision set and lost EUR 0.10 when drawing a white ball. In the win frame condition, participants won EUR 0.10 when drawing a right ball without having an initial endowment. Furthermore, participants in the promotion condition received result messages like "You have won 0.10 MU" (e.g., MU: monetary units) or “You did not win 0.10 MU”, and in the prevention condition they received result messages like "You have not lost 0.10 MU" or "You lost 0.10 MU". To compare the induced situational framing, I let the participants play each condition randomly (40 rounds promotion condition, then 40 rounds prevention condition, or in the other way round).
In the second step, the participants played one round of the Brown–Peterson distraction task (Peterson & Peterson, 1959) to avoid direct framing or memory effects, before they played the second version of our urn game. The distraction task took about 30 seconds, and the working memory of the participants is overwritten, while they are asked to remember two trigrams, while subtracting values from a number. A correct answer in the task was rewarded. Finally, the participants were faced with a variation of the urn game to measure their capabilities in Bayesian Updating (Alós-Ferrer & Hügelschäfer, 2012). In this version of task 1 the computer choses an urn in the first round and draws a series of balls randomly from this urn with replacement. After each draw, participants estimated the posterior probability that this is the predominantly "black" urn. This task is a common procedure to measure participants capabilities in Bayesian updating and conservatism, introduced by Phillips and Edwards (Phillips & Edwards, 1966). To incentivize participants, correct answers (+/- 5 per cent error tolerance) were rewarded with a small monetary pay-off at the end of the task. The accuracy of the estimates is measured by the mean deviation between the correct Bayesian posterior probability and the estimates over all draws (difference between objective and subjective probability).

4.5.2 Participants

54 adult participants (30 male, 24 female, age range=17-30, M=21.74, SD=2.54) took part in the experiment at the Karlsruhe Decision and Design Lab. The participants were recruited from our student pool from the Karlsruhe Decision and Design Lab, and received a participation fee of 2.00 Euro, a payment of 3.00 Euro for the questionnaire, and a performance-based payment of 0.10 Euro for each drawn black ball or correct answer. Mean pay-off was 10.85 Euro (SD = 1.04). The knowledge quiz and the experimental tasks took approximately 30 minutes.

4.5.3 Procedure

To address my hypotheses, I carried out the following experiment, which consisted of three steps (see Figure 29). Approximately two weeks prior to the experiment, participants registered for our experiment. By registering a specific time for their participation, they registered randomly for a treatment. After registering, and they were asked to participate in an online questionnaire. They were told that they would receive 3 Euro on the day of the experiment for filling out the questionnaire until one week before. In the questionnaire, I measured faith in intuition (Keller, Bohner, & Erb, 2000) and demographics. The online questionnaire was implemented in Limesurvey (Schmitz, 2012).

Figure 29: Procedure of the experimental investigation of Study 2

The procedure of the experiment was based on that of the previous study (see Section 4.4). The instructions were presented on the computer. Half of the participants were first provided with an introduction consisting of the urn game in a win frame, followed by the urn game in a loss frame. The other half of the participants received the same instructions, but in the opposite order. Before the experiment, participants had to answer control questions to ensure they understood the general procedure of the experiment. The decision tasks (urn game and Bayesian updating game) were prepared in the KD2Lab using a computer version of the experimental task as done by Alós-Ferrer et al. (2016). The computer version was implemented with Brownie following the Brownie standard guideline for the design and implementation of computer-based experimental tasks (Jung, Adam, et al., 2017).

4.5.4 Results

To measure decision inertia, I compared again mean rates of suboptimal behaviour in case of divergence and convergence between inertia and Bayesian updating (26.3 per cent, SD=24.9; 7.4 per cent, SD=12.4), respectively. A two-tailed Wilcoxon signed rank test indicated that the former error rate was significantly higher than the latter ($n = 54, Z = 5.39, p < .001, r = .73$). Previous studies (see Alós-Ferrer et al. (2016), or Study 4.4) report similar error rates, indicating that I could reproduce the inertia effect reliably in my setting. However, if I compare errors between the win and loss-framing condition (see Figure 30), a Wilcoxon signed rank test found no significant differences between Bayesian updating and decision inertia.

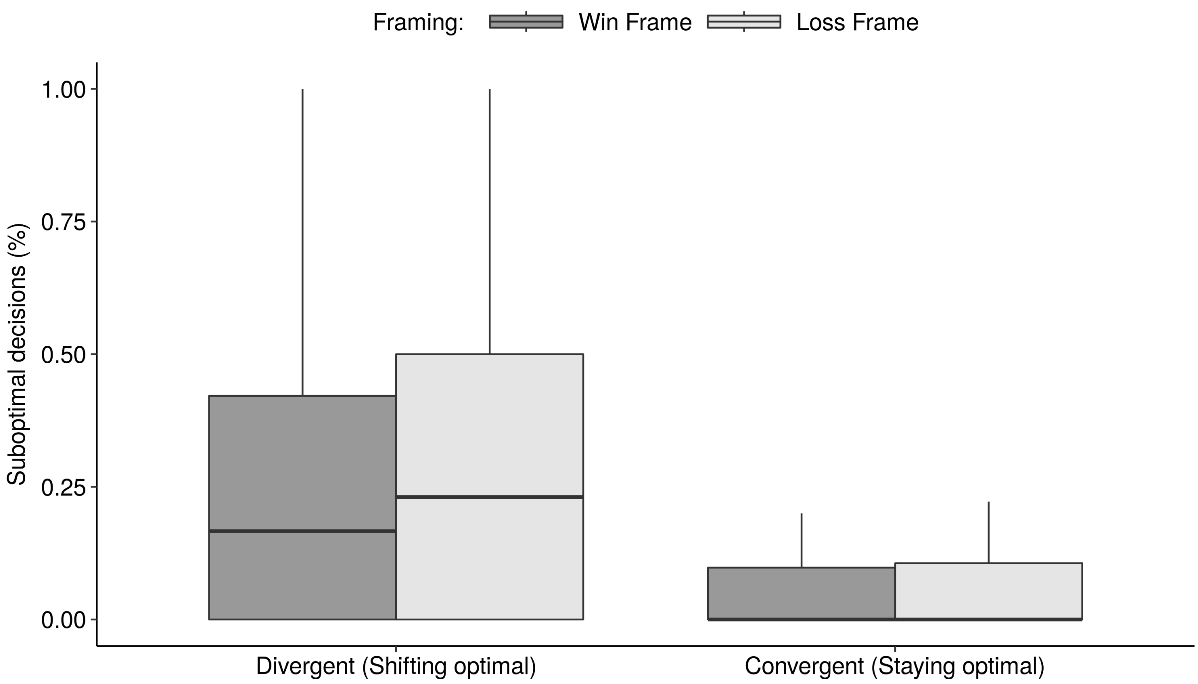


Figure 30: Comparison of the two framing treatments in Study 2.

Regarding error distributions at the individual level, I found inter-individual heterogeneity (Achtziger et al., 2015; Charness & Levin, 2005), best represented by two clusters of participants. Across both conditions, one large group of participants exhibited error rates above 25 % and one smaller group showed error rates of about 60 %. Similar results have been reported (Alós-Ferrer et al., 2016), indicating that the participants did not respond randomly, and that I could reproduce the decision inertia effect reliably.

In the investigation of the influence of the cognitive drivers on decision inertia, all participants had to complete a web-based questionnaire until one week before the experiment. In this questionnaire, I measured participants' faith in intuition beforehand (mean=3.3, SD=0.6, α=0.84). Furthermore, I standardized (z-transformed) all variables and ran a random-effect probit regression on second-draw errors to investigate the relationships between skills in Bayesian updating, faith in intuition, and framing. I conducted a random effect regression on suboptimal decisions to account for the individual observations. The lack of Bayesian updating skills was computed as the mean difference between objective and subjective probability (as described above).

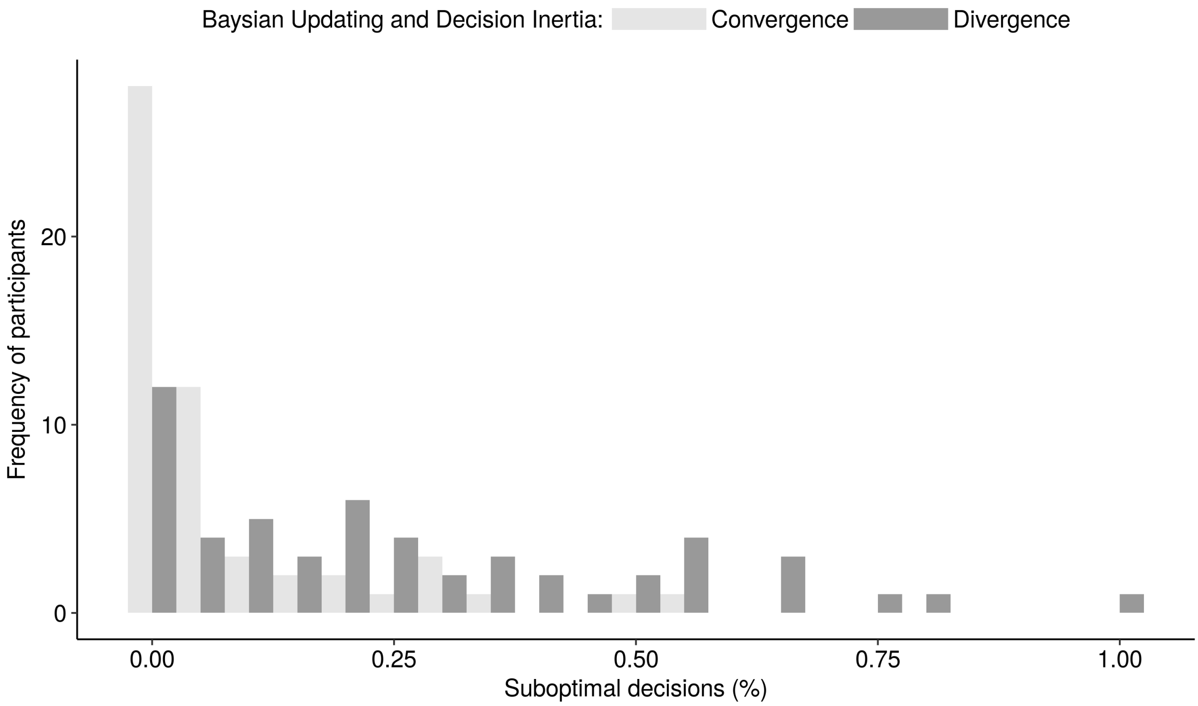


Figure 31: Cross-treatment comparison of suboptimal behaviour in free and forced draws.

Table 16: Random-effects probit regression on suboptimal behaviour (1=suboptimal).

Variable	**Beta (SE)**	**P**
(Intercept)	-2.18	< 0.001 ***
Divergence (1=True)	1.07	< 0.001 ***
Framing (1=Loss, 0=Win)	0.28	0.03 *
Lack Of Bayesian Updating Skills	0.19	0.16
Faith in Intuition	-0.03	0.81
Trial Number	-0.03	0.41
Gender (1=Female)	0.36	0.14
Divergence x Framing (1=Loss, 0=Win)	-0.12	0.44
Divergence x Lack Of Bayesian Updating Skills	0.07	0.38
Divergence x Faith in Intuition	0.20	< 0.01 **

Number of obs: 2160; **random effect:** participant id, **participants:** 54; **Tjur's D** = .27, **Signif. codes:** 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.5.5 Discussion

Considering the direct effects on suboptimal decisions, I found a significant positive effect of framing on suboptimal decision-making, suggesting that participants with an induced prevention focus are more likely to make more suboptimal decisions in the urn game. The significant influence of divergent processes shows that divergence of cognitive processes increases suboptimal decisions (decision inertia). However, I found no significant effect of Bayesian updating skills or faith in intuition on suboptimal decision-making in my task. If I consider the drivers of decision inertia, by examining the interaction effects of process divergence with the three other factors, the results show a significant effect of framing of an individual's tendency to rely on heuristic processing (faith in intuition), but no significant effect of skills in Bayesian updating or loss framing.

4.6 Distinguishing Cognitive and Motivational Drivers of Decision Inertia

To build on my findings in Section 4.4 and 4.5, and to disentangle cognitive and motivation drivers of decision inertia and addressing the remaining hypotheses, I carried out a second experiment including three tasks: one task to measure decision inertia (Task 1) as in Section 4.4, followed by two additional tasks that measured individual evidence threshold (Task 2) and performance in probability updating (Task 3). This experimental task has been used reliably to induce decision inertia and allows me to compare my present findings with those of my first study. In my third study, participants were again faced with two urns, each with each six balls that could each be black or white, and there were two different options for how black and white balls were distributed in the urns.

4.6.1 Method

In this setting, I also planned to investigate the influence of decision autonomy on decision inertia (H1b). Hence, the first task took the same setting as in the first experiment (see Section 4.4), but with the addition that participants were faced with free or forced draws alternately. This experiment replicates the urn game by Alós-Ferrer et al. with forced and free decisions (Alós-Ferrer et al., 2016). The first choice was either left to the decision-maker or made by a computer. Because free choices result in higher commitment, this setting allowed us to investigate the influence of commitment-induced consistency on decision inertia (H1b). Furthermore, this method allowed us to compare the findings to the original setting from Alós-Ferrer, and to differentiate between autonomous and required decisions.

In the second and third tasks, participants were faced with variations of the urn game of Task 1 (different distributions of black balls and number of balls per urn). In the second task designed to measure evidence thresholds, participants were given an additional option in the first draw. They could draw as many balls as they liked from the first urn (with replacement), thus increasing their knowledge of the probable state of the world. However, each additional draw incurred a small monetary penalty. For each of a series of trials, I identified the point when the participants stopped sampling in order to play the lottery. To allow for a test of H5, the number of balls drawn consecutively was used as a measure of the participant's subjective individual decision threshold or "desired level of confidence".

In the third Bayesian updating task (see Study 2), the computer chose an urn in the first trial and drew a series of balls randomly from this urn with replacement. After each draw, participants estimated the posterior probability that this is the predominantly "black" urn, resembling the probability-updating task introduced by Phillips and Edwards (Phillips & Edwards, 1966). Correct answers were again rewarded with a small monetary pay-off at the end of the task. As before, the accuracy of participants' estimates was measured by the mean deviation between the correct Bayesian posterior probability and the estimates over all draws (difference between objective and subjective probability).

Afterwards, participants had to respond to a questionnaire addressing motivational personality traits (preference for consistency, action orientation) and demographical factors to replicate our findings from Study 1. Between the three experimental tasks, participants were given a distraction task to avoid cognitive depletion and to reduce carry-over effects. This task was a computer-based version of a short-term memory task introduced by Peterson and Peterson (L. Peterson & Peterson, 1959) and was given once between the three main tasks. Participants were faced with two trigrams (number and characters) and had to subtract 3 from the number trigram each time a ball appears. Subsequently, they were asked to repeat one of the trigrams randomly.

4.6.2 Participants

101 adult participants (56 male, 45 female, age range=19-37, M=22.8, SD=2.95) took part in the experiment at Karlsruhe Decision and Design Lab. The participants received a performance-based payment of 0.10 Euro for each black ball in the main task or correct answer in the distraction task and 0.50 Euro for answering the questionnaire. Mean payoff was 14.07 Euro (SD = 1.82). The experiment took approximately 60 minutes.

4.6.3 Procedure

The procedure of the experiment was based on the previous study. I again followed the design of Alós-Ferrer et al. (2016). Participants had to play two types of two-draw situations. In the first type, participants could choose the first urn by themselves. In the second type, participants were confronted with a random choice from the computer. Because I wanted to reduce confounding effects, I varied choice sets alternately. After receiving the instructions, and passing the first questionnaire, the participants played the two-draw urn game 80 times (160 draws). The decision task, instructions and questionnaires were replicated according the descriptions of Alós-Ferrer et al. (2016). Next, the participants played one round of the distraction task (L. Peterson & Peterson, 1959), followed by the evidence threshold task.

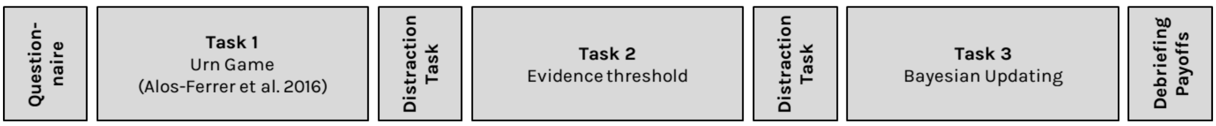


Figure 32: Procedure of the experimental investigation of Study 3.

According to H5, I assume that participants differ in the amount of information or evidence they need to make a decision (= decision threshold value). Therefore, I no longer reduced the decision to two subsequent decisions, but gave the participants the opportunity to take balls from one urn several times before they had to make a final decision.
Finally, after a further round of our distraction task, the Bayesian updating task was presented. In this last task, the participants were faced with five sets of samples drawn by the computer. The participants were shown the draws successively. After each draw, they were asked to indicate the correct Bayesian probability of the urn being the predominately black one. The

samples were drawn randomly from the computer and consisted of 10 balls. All participants played the same five sets (see Appendix C).

Afterwards, the participants were asked to complete three questionnaires. Because of the low internal consistency of preference for consistency in the first study, I used a questionnaire originated by Cialdini et al. (1995). In contrast, the previous action- and state-orientation (see Kuhl (1994b), appendix Table 25) and demographics questionnaire were the same as in Study 1 and Study 2.

4.6.4 Results

To measure decision inertia, I compared again mean rates of suboptimal behaviour in case of divergence and convergence between inertia and Bayesian updating, resulting in error rates of 24.0 % (SD=24.1) and 8.7 % (SD=11.6), respectively. A two-tailed Wilcoxon signed rank test indicated that the former error rate was significantly higher than the latter ($n = 101, Z = 7.5792, p < .001, r = .75$). These observations replicate previous results.

Furthermore, I checked for significant differences between the two choice sets (free vs. forced first draw, H1b). The findings show that the differences in mean error rates remain significant for both sets (free draws: $Z = 7.709, p < .001, r = .77$, forced draws: $Z = 5.4178, p < .001, r = .54$).

Comparing errors between the free and computer-provided choices (see Figure 1), a Wilcoxon signed rank test found significant differences in case of convergence ($Z = 5.0519, p < .001, r = .50$), but not in case of divergence between Bayesian updating and decision inertia ($Z = 0.96841, p > .05, r = .10$). The findings are in line with previously published findings on effects of free choices on decision inertia (Alós-Ferrer et al., 2016).

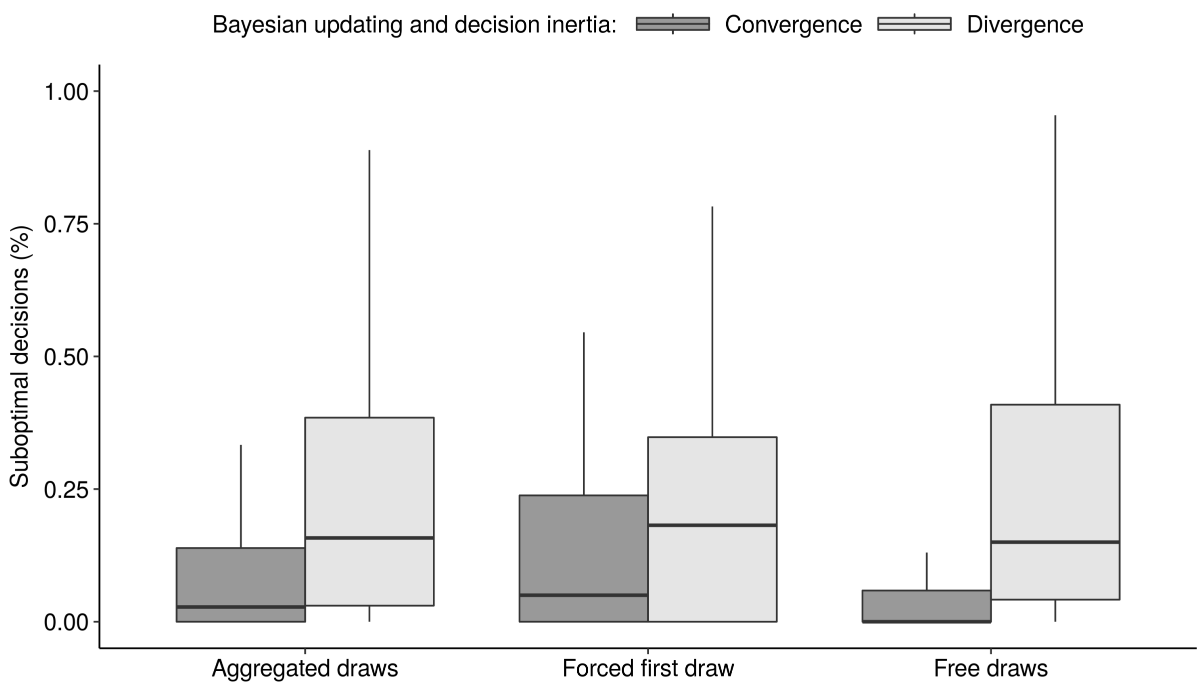


Figure 33: Cross-treatment comparison of suboptimal behaviour in free and forced draws.

As before, I investigated the error distributions at an individual level. Again I found strong inter-individual heterogeneity, indicating that the participants differ considerably in their decision-inertia proneness.

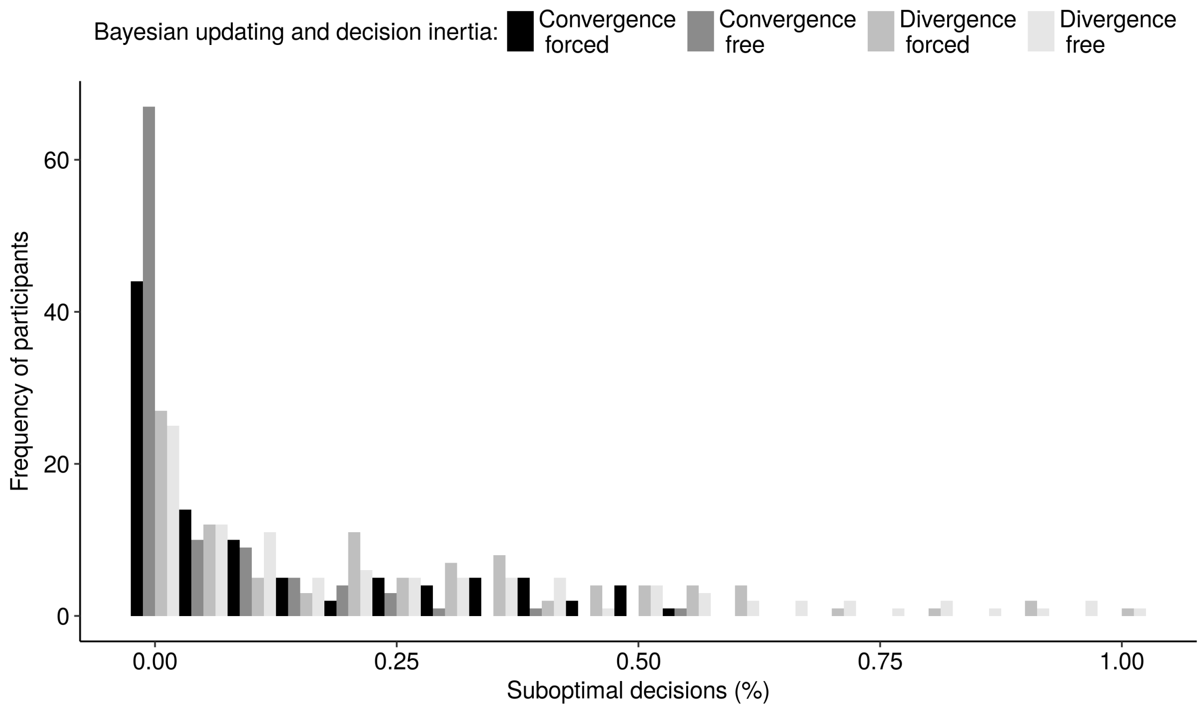


Figure 34: Frequency of suboptimal behaviour in case of convergence or divergence with decision inertia.

To investigate motivational drivers of decision inertia, I measured different personality traits. The preference for consistency score (mean=5.87, SD=1.22, α=.84, 9-point Likert item scale), and action orientation (mean=0.49, SD=0.19, α=.78, binary item scale) had sufficient internal consistency as measured by Cronbach's alpha.
As in Study 1, I conducted a probit regression on suboptimal behaviour with divergence between decision inertia and Bayesian updating as a dummy variable. This approach allows us to compare the influence of our variables on decision-making in general (convergence, dummy variable = 0) and on decision inertia in particular (divergence, dummy variable = 1). I used the variable "Number of draws required for a decision" as a proxy for the evidence threshold in Task 2. This variable reflects the mean number of draws participants make before they decide upon one of the urns. To investigate the influence of decision autonomy (H1b), and because of the different error rates in our choice sets, I run two different probit regressions (Model 1 without a dummy-variable, and Model 2 with a dummy variable indicating whether the first decision was free (forced draw=False) or not (forced draw=True). The lack of Bayesian updating skills was computed as the mean difference between objective and subjective probability (as described above).

Table 17: Random-effects probit regression on suboptimal behaviour (1=suboptimal).

Variable	Beta (SE)	P	Beta (SE)	P
	(1)		(2)	
(Intercept)	-1.97	< 0.001 ***	-2.5	< 0.001 ***
Action orientation	-0.07	0.35	-0.08	0.30
Divergence (1=True)	0.64	< 0.001 ***	0.89	< 0.001 ***
Preference for Consistency	0.01	0.84	0.02	0.81
Lack of Bayesian Updating Skills	0.21	< 0.01 **	0.23	< 0.01 **
Number of Draws to Decide	-0.28	< 0.01 **	-0.32	< 0.001 ***
Trial Number	-0.06	< 0.001 ***	-0.07	< 0.001 ***
Gender (1=Male)	-0.16	0.21	-0.20	0.18
Forced Draw (1=True)	-	-	1.13	< 0.001 ***
Divergence x Forced Draw	-	-	-0.39	< 0.001 ***
Divergence x Action-orientation	0.16	< 0.001 ***	0.19	< 0.001 ***
Divergence x Preference for Consistency	-0.01	0.65	-0.02	0.58
Divergence x Lack of Bayesian Skills	0.01	0.72	0.00	0.87
Divergence x Number of Draws to Decide	0.02	0.62	0.05	0.39

Number of obs: 16160; **random effect:** participant id, **participants:** 101; **Tjur's D (1)** = .122
Tjur's D (2) = .188; **Signif. codes:** 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Considering the non-interaction predictors, I observe a significant negative effect of the trial number ($p < 0.001$) and a positive effect of divergence ($p < 0.001$), replicating our corresponding results in Experiment 1. Furthermore, I see a significant positive effect of low Bayesian updating skills on suboptimal behaviour in general. Moreover, there is a significant negative effect of the number of draws before a participant decided on an option.

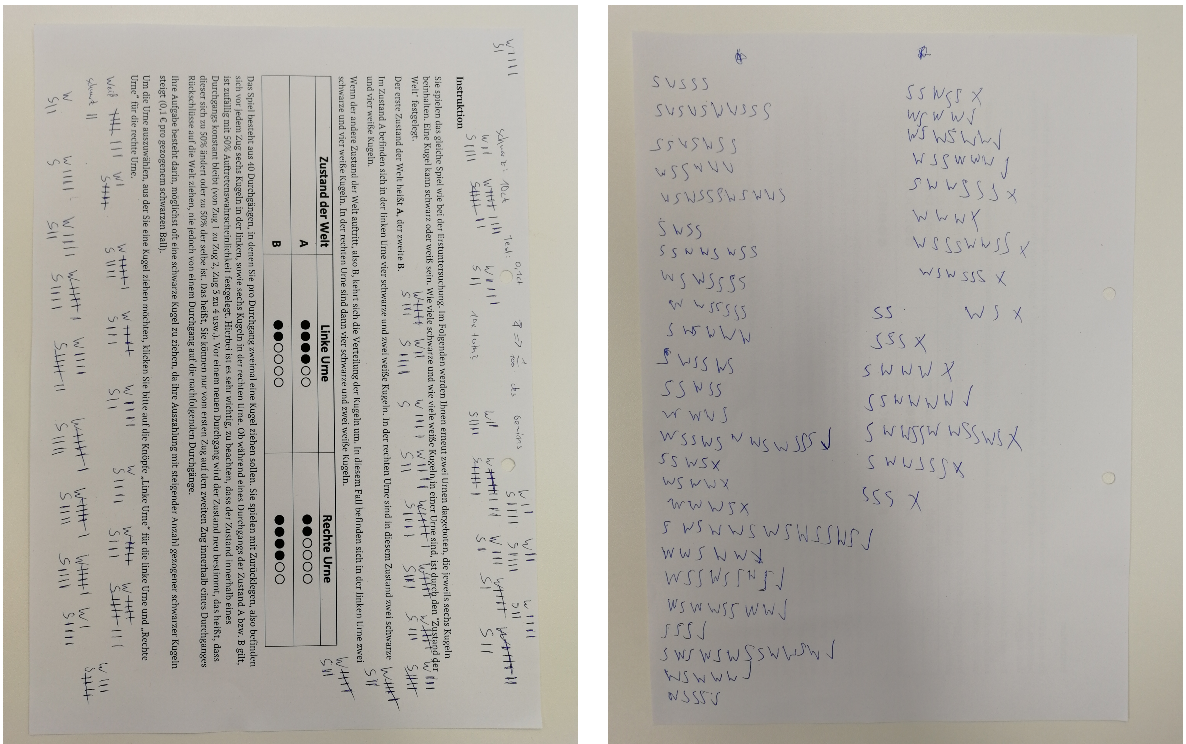
If I consider the interaction of divergent processes with the other variables to investigate the drivers of decision inertia (choice repetition, when switching is better), I find again a significant positive relationship between decision inertia and action-orientation. Because action-orientation is only significant in the case of interaction with divergent processes, this indicates only a significant positive influence of action-orientation on decision inertia or the tendency to repeat a decision regardless of the outcome. Furthermore, I found a significant negative influence of forced draws on decision inertia, but a positive influence on suboptimal decision-making in general.

4.6.5 Discussion

I observed significant negative effects of Bayesian updating skills on suboptimal decisions in general but no specific effect when decision inertia diverged from Bayesian updating. The significant negative effect of number of draws until a decision was made indicates that higher decision thresholds decreased the likelihood of suboptimal decisions. In addition, the results show that the interaction effect of divergence with decision inertia and action-orientation is significantly positive. This finding suggests that action-oriented participants are more likely to rely on decision inertia in situations when decision inertia and Bayesian updating suggest different behaviours.

In the second regression analysis (Model 2), I considered decision autonomy. The significant effects suggest that lack of decision autonomy increased suboptimal decisions in general, but decreased the tendency to rely on decision inertia. Thus, decision makers who make their first choice freely exhibit more decision inertia later on. As in Experiment 1 (see Section 4.4), I found no significant influence of preference for consistency on decision-making or decision inertia.

I would like to use this concluding section of Chapter 4 to point out another very unusual behaviour of a small minority of the participants in my studies. In most of the pretests and in all my studies investigating decision inertia, a small percentage of participants (about 5 %), tried to find a pattern between the data-generating process of the urn game. The participants used the instructions or the provided papers to note which urns had given which result and when (see Figure 35). However, since this is a random process, the results of the urns cannot be predicted beyond the two draw decision. This was clearly communicated and also asked about in the knowledge task questions.



(a) front. **(b)** back.

Figure 35: Notes of one of the participants in the pretest study of part 2. The different results of the urns have been noted, which suggests that the participant did not understand the concept of random draw.

This unusual behaviour suggests that there must be other mechanisms besides the drivers under consideration that can cause decision inertia. Here the question arose whether the cognitive aspects of decision-making could not play a greater role after all, especially with regard

to the understanding and handling of statistics and statistical information by test subjects research in the field of experience sampling (Kaufmann, Weber, & Haisley, 2013), in particular, suggests such processes and shows that the related errors can be reduced through training.
In sum, I found that suboptimal decision-making in general depends on an individual's (lack of) cognitive capabilities in Bayesian updating and the amount of information an individual requires to reach a decision. However, these results do not hold for decision inertia specifically. For decision inertia, I found significant interactions of individual differences only in action-orientation and experimentally induced decision autonomy. Furthermore, other possible causes of decision inertia like a preference for consistent information did not receive empirical support. This indicates that decision inertia is possibly not a consequence of consistency-seeking or the commitment process or the cognitive inability to process the new information correctly. Instead it might be the result of the role negative or dis-confirming information plays for the individual.

5 Part III: Overcoming Decision Inertia in Robo-Advisory

***Abstract**. Modern financial planning tools like robo-advisors claim to support user's wealth management. This study relied on a choice architecture approach to investigate the benefit of robo-advisors in investment support and to overcome biased financial decision-making, in particular towards decision inertia in investment decisions. A robo-advisor was constructed and a simple market simulation was built to investigate the effectiveness of two digital nudges (defaults and warning messages). Furthermore, I controlled for confounding variables (e.g., financial literacy or risk aversion). The results indicate a significant influence of both nudges on reduced decision inertia. This finding indicates a possibility of reducing financial decision inertia through robo-advisor design, and it suggests that financial planning tools can help users to overcome their financial decision biases.*[3]

5.1 Decision Support and Financial Decision-Making

The self-directed investment of users on capital markets in order to save, for example, for a pension or to become a home owner, is a complicated matter for most private investors (Looney & Hardin, 2009; Wood, 1986). Current research provides ample evidence that decision-makers are overwhelmed by this kind of multi-criteria decision problem (Minch & Sanders, 1986) and because of their limited cognitive capacities, they tend to make an effort-accuracy trade-off (Johnson & Payne, 1985; Looney & Hardin, 2009). This implies that decision-makers are basically striving to keep the effort associated with a decision as low as possible. On the other hand, however, they try to maximize the result. Decision-makers often face tension between deliberative and effortful processes, on the one hand, and intuitive and effortless processes, on the other (Alós-Ferrer & Strack, 2014; Kahneman, 2003). As a consequence of this conflict, decision-makers often rely on the intuitive decision-making processes in complex decision-making situations (Gigerenzer, 2008). In particular, it is argued that this tendency results from simpler and less strenuous cognitive processes. This interplay of deliberative and intuitive processes systematically shapes economic decisions, and has been used as theoretical explanation for different decision anomalies in various studies in behavioural economics and finance (Alós-Ferrer & Strack, 2014; Dhar & Gorlin, 2013; Barberis & Thaler, 2003).
Considering financial decisions in particular, it is well known that effort-accuracy trade-offs cause decision makers to rely on heuristics or rules-of-thumb instead of deliberative decision-making (Gigerenzer, 2008; Thaler & Benartzi, 2004; Thaler, 1980). While it may be a great advantage of heuristic (financial) decisions that they can be made quickly, automatically, and with little effort since they solve problems by simplification (Tversky & Kahneman, 1975), they consequently also lead to potentially suboptimal decisions. Experimental findings show that this observation holds true both for economic decisions under uncertainty (Looney & Hardin, 2009; Tversky & Kahneman, 1975, 1971) and for those under certainty (Thaler, 1999, 1985). In particular, financial advisory research reports numerous studies providing a wide range of

[3]***Note**. The content of this section is a revised version of Jung and Weinhardt (2018) and Jung, Erdfelder, and Florian (2018), which were created in the course of this thesis. Other sources of this section are marked as such.*

evidence that private investors make simplified assumptions and deviate systematically from rational behaviour. In recent years, numerous biases in the field of asset management have been identified (Bhattacharya, Hackethal, Kaesler, Loos, & Meyer, 2012). Take, for instance, that private households have a tendency to underdiversify portfolios (Calvet, Campbell, & Sodini, 2007; Ahearne, Griever, & Warnock, 2004), they shy away from taking risks (Badarinza, Campbell, & Ramadorai, 2016), and they have a general tendency to follow inertia in investment decisions (Calvet et al., 2007; Madrian & Shea, 2001).

In sum, it is widely accepted among researchers that most heuristics can lead to systematic errors in financial decision-making (see e.g. Calvet et al. (2007); Barber and Odean (2000)). However, the crux of this issue is that many investors are unaware of this fact. Those investors who would have a need for advice to overcome these mistakes, or to discover them do not seek that advice (Bhattacharya et al., 2012). Specifically, the investors, who need help the most, do not consider taking it. On the one hand, this decision may have justifiable reasons, such as the fact that private investors often consider investment advice to be expensive, biased, or manipulative. On the other hand it is also a reason for distrust regarding investment advice in general (Bhattacharya et al., 2012). High fees in particular, can massively reduce the profitability of seeking consultation; an expensive consultation can even become a loss for the private investor (French, 2008).

In the past, so-called exchange-traded funds (ETF) were intensively discussed as a possible panacea for this problem (see Bhattacharya et al. (2012); Boldin and Cici (2010); French (2008). These financial products mirror the performance of an index, or market, or industry sector. This is mostly done automatically and therefore, unlike an actively managed fund, traditional ETFs do not need a human decision maker such as actively deciding portfolio managers. The missing fees for an active manager makes ETFs also cheaper compared to actively managed funds. Hence, ETFs offer an advantageous way to invest in a highly diversified portfolio, a reasonable strategy for the average investor (French, 2008).

As a result, many investors are increasingly relying on ETFs. The problem, however, is that even these new alternative forms of investment are rarely used profitably by private investors, as they are either sold or bought at the wrong time, or unfavourable products are selected (Bhattacharya et al., 2012). Other studies suggest that the cost of ETFs can vary substantially (Hortaçsu & Syverson, 2004), or that private investors tend to prefer more expensive ETFs (Elton, Gruber, & Busse, 2004). Moreover, investors can choose from a large number of ETFs, so it may be difficult to make an appropriate instrument selection. Current research suggests that despite the simplification of investment products for investors, cognitive biases can still arise (Bhattacharya, Loos, Meyer, & Hackethal, 2016). As a solution to this dilemma, and in order to provide investors with low-cost products and high-quality advice, so-called robo-advisors are being discussed in recent decision support research (see Section 1).

If private investors have a tendency to make biased investment decisions, and if external investment advice can give them unbiased support and help them to overcome their mistakes, private investors would benefit from low-budget, automated investment advice. Robo-advisors are online platforms that have exactly this purpose and are intended to support investors in their investments. By means of various user assistance components, investors are guided through an automated self-assessment process (Phoon & Koh, 2017; Sironi, 2016). As a result of the self-assessment process, various investment alternatives are proposed to the user, and these alternativesare further maintained in accordance with the user's strategy through various rebalancing techniques. In general, a distinction is made between passive and active robo-advisors. While active robo-advisors let the user decide upon the execution of the investment strategy, passive robo-advisors invest in a certain strategy that is maintained and can be changed only by user intervention.

Compared to traditional investment advisory, robo-advisors thus offer independent financial advice, since most robo-advisors act only as a platform between clients and financial product providers (Phoon & Koh, 2017). In addition, robo-advisors currently offer ETFs only as an investment option, passively managed and thus enabling low costs to be realized. The savings are eventually passed on to the users. Inexperienced investors benefit from robo-advisors, especially, as robo-advisors present information in an understandable way and offer a cost-effective alternative to traditional financial advice.

Although it seems that robo-advisors reduce many of the problems associated with traditional financial advisory, there is also the risk of cognitive biases. This risk is all the more relevant when one considers that inexperienced investors are the primary target group of robo-advisors. As such, robo-advisors could be a pitfall for many private investors, in particular. Therefore, it is of utmost relevance for these systems that biases are not fostered by the design of the choice environment. Research in behavioural economics and choice architecture suggests that unwanted biases can be successfully reduced through the design of the choice environment of the decision-makers (Johnson et al., 2012; Thaler & Cass, 2008). Thus, the choice environment in which the decision is made can be changed and clearly controlled in robo-advisors. It is this possible, from a design point of view, to provide controlled advancement of certain cognitive biases. In other words, an inertia-sensitive design for robo-advisors reduces suboptimal decisions in advance rather than postponing them to a later time.

5.2 Designing Digital Nudges for Decision Support Systems

Information systems research illustrates that decision support systems like recommendation agents, can help users make better-informed and less-biased decisions. For instance, recommendation agents can help users to screen large sets of products enabling them to find preferred products with little search effort (Häubl & Trifts, 2000). Another recent study illustrates that tagging messages of a recommendation agent with social information can facilitate information retrieval (Kretzer & Maedche, 2018).

An additional advantage of recommendation agents is that they allow influencing the decision-making of their users in a controlled and predictable manner (Johnson et al., 2012). Findings from behavioural economic research suggest that a choice is not made independent of environment, but that it is directly influenced by the way it is embedded, structured, and presented in the environment (Johnson et al., 2012). Examples include listing specific products alongside other alternatives (Cooke, Sujan, Sujan, & Weitz, 2002); or by making specific products more salient, the preferences of the users can change (Häubl & Trifts, 2000).

The theoretical groundwork for the design and development of such bias-sensitive systems is established by choice architecture (Thaler et al., 2014; Johnson et al., 2012). Choice architecture is a theoretical framework to deliberately design the choice environment of decision makers and to improve it for the decision makers' benefit. Building on findings from dual-processing theory (Alós-Ferrer & Strack, 2014; Kahneman, 2003), choice architecture postulates two different types of cognitive processing that build up the intention of users: an intuitive system that is fast but heuristically driven, and another slow and rational system that is able to compute deliberative decisions. Behavioural economics classifies the first type of automatic decision-making as "System 1", and the second type as "System 2" (Thaler & Cass, 2008; Kahneman, 2003). Intention building, or which of the systems will dominate the decision-making process, also depends largely on the choice environment. As this choice environment thus relevantly influences users' decisions, choice architecture aims to systematically design this environment (Johnson et al., 2012). Just as an architect designs a house for the future residents and designs rooms and pathways according to the needs of the inhabitants, a choice architect should build the choice environment in accordance with the users' needs (Thaler et al., 2014). The choice environment should guide users to the best option, which should be as easily accessible as possible (Thaler et al., 2014; Johnson et al., 2012).

Choice architecture provides a plethora of interventions to make information systems as helpful as possible for their users. For this purpose, techniques like defaults, framing, or anchoring are proposed to design the choice environment, and hence to push the user of an information system to a specific decision outcome (Weinmann et al., 2016; Jameson et al., 2014; Johnson et al., 2012). The systematic use of these tools is called nudging. Research suggests that users are generally more willing to accept these types of interventions, because the users do not feel limited in their freedom (Johnson et al., 2012), in particular, when users benefit from them. Hence, choice architecture can provide a theoretical foundation to design decision support systems to reduce the effect of biases like decision inertia in decision-making (Jameson et al., 2014; Thaler et al., 2014; Johnson et al., 2012).

In financial decision-making, choice architecture approaches have been successfully used to reduce biases by considering them in the design strategy (Thaler et al., 2014; Silver, 1990) of the information system. For instance, Looney and Hardin illustrate that myopic loss aversion can be reduced by the design of a financial planning tool (Looney & Hardin, 2009). Or Bhandari et al. have illustrated the general, positive influence of decision-support systems in debiasing investors in financial decision-making (Bhandari, Hassanein, & Deaves, 2008).

A further idiosyncrasy of human judgement and decision-making that has serious implications for financial decision-making but has received less research interest is decision inertia, or the tendency to repeat a previous decision, regardless of the outcome (Alós-Ferrer et al., 2016; Dutt & Gonzalez, 2012). However, a recent review illustrates that decision inertia reflects an important aspect in economic decisions (Erev & Haruvy, 2013). Decision inertia is discussed as a possible explanation of the psychological processes that lead decision-makers and potential investors to repeat a suboptimal decision (Alós-Ferrer et al., 2016; Charness & Levin, 2005). For instance, in a study of entrepreneur and non-entrepreneur investment behaviour, Sandri et al. report an inertia effect manifesting in the tendency to hold a suboptimal investment, regardless of rational considerations about risks of loss (Sandri et al., 2010). Sautua reported decision inertia in an economic lottery game (Sautua, 2017). In the experiment's task, the participants repeated their previous decision even if it was economically suboptimal in a subsequent period. Additionally, in consumer decision-making, economic research observes a form of consumer persistence to buy the same product multiple times (Dubé, Hitsch, & Rossi, 2010). Also, however, many different studies evaluating financial decisions of private households illustrate that inertia also leads to suboptimal decisions in financial planning and decision-making (Agnew, Balduzzi, & Sunden, 2003; Madrian & Shea, 2001). Furthermore, the cognitive foundations of inertia in subsequent decision-making have received no attention so far. The actual triggers of decision inertia remain uncleaer (Alós-Ferrer et al., 2016). In addition, only a few papers that allow conclusions as to how decision inertia or similar behaviour can be reduced (Alós-Ferrer, Hügelschäfer, & Li, 2017).

Even if decision support literature suggests that biases can be reduced by information system design (Weinmann et al., 2016), it remains unclear whether and how these findings can be transferred to robo-advisors. In particular, the question arises whether they can be applied there at all, or whether nudges have a different effect in other semantic contexts. For example, framing is seen as one of the central tools of choice architecture (Johnson et al., 2012). However recent studies show that the influence of framing is not stable (Fagley & Miller, 1990) and that framing effects do not always work. The influence of framing depends on gender, risk-taking and cognitive style. Not only on a general level with regard to nudging, but also specifically for decision inertia, contradictions can be found in the literature. Thus, various studies (Welsh, Ordóñez, Snyder, & Christian, 2015; Zhang et al., 2014) each report an exactly opposite effect of framing on inertia of decision in a moral context.

The above summary of the literature underlines a clear need to investigate and validate various nudging or debiasing techniques in a bias-specific and application-specific manner. Figure 36 illustrates the theoretical relationships of the approach of this study that has been discussed in this section. Based on the raised research question (RQ3), the aim is to design a robo-advisor sensitive to financial decision inertia. For that purpose, this study relies on nudges that directly influence the financial decision-making of the users, and should help them to overcome decision inertia, when it is necessary (Johnson et al., 2012). Nudges are design features that support effortless and automatic processing towards a direct decision (Thaler et al., 2014).

5.3 Robo-Advisory Design and Hypotheses Development

The main purpose of this experimental study is to investigate the influence of the derived nudges (implemented by two design features) on decision inertia, and (sub-) optimal investment decisions in the context of a robo-advisor. The research model in Figure 36, illustrates the relationship of the different nudges implemented by different design features, and individual's tendency to rely on decision inertia, which can be objectively measured by valuations that are contrary to the Rational Utility Theory (see experimental design below).

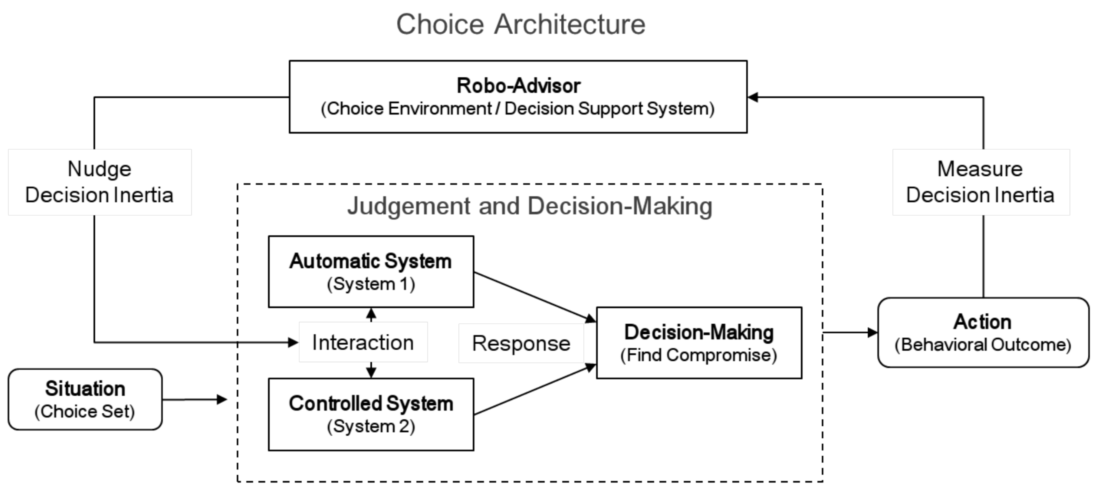


Figure 36: Research framework for this investigation (adopted from Section 1).

The implemented nudges of the choice architecture toolbox and the resulting choice environment are part of an overarching system design to guide decision makers through a decision process (Silver, 1991). This work aims to design the choice architecture of the financial decision support system to nudge decision-makers to have less decision inertia. In the next part of this work, the hypotheses based on the tools of the choice architecture are illustrated.

5.3.1 Default Nudge (H1)

A choice architecture approach to design the choice environment sensitive to inertia in decision-making requires addressing the behavioural drivers of the tendency to repeat a decision (or option) without shifting away. The rationale behind this approach is that people rely on heuristics and inertia because they do not want to expend cognitive resources.
Choice architecture research suggests that defaults are an appropriate tool to counter-act this suboptimal behaviour by nudging people towards other heuristic processing (Johnson et al., 2012). When deciding between different options, where one of them is pre-selected, decision-makers tend to rely on the default heuristic (Johnson & Goldstein, 2003), which means that they usually choose the default option a significant number of times. Following this rationale, this study assumes that if decision-makers show decision inertia, they repeat a previous investment without considering the alternatives. If the optimal decision is pre-selected and if that option is not the previous one, however, decision inertia and the default bias are in conflict. Based on the choice architecture literature, it is assumed that this situation results in the behaviour that the decision-maker *repeats* the default instead of the previous decision. Many different studies in the field of behavioural design support these conclusions. So far, defaults are also successfully applied in other scenarios to nudge people to certain behavioural changes. For instance, Stryja et al. (see Stryja, Satzger, and Dorner (2017); Stryja, Dorner, and Riefle (2017)),

proposed defaults and priming as possible nudges to overcome the resistance to change in innovation acceptance. In their study, default nudges significantly influenced resistance to acceptance of electronic cars (Stryja, Satzger, & Dorner, 2017). In another study, the tendency for air travellers to pay for carbon-offsets could be increased by default nudges (Brouwer, Brander, & Van Beukering, 2008).

Another point is that defaults could also be perceived as choice recommendations. As a result, decision-makers who are uncertain of their decisions, or who do not know how best to decide, perceive the default as a socially desired option and are therefore more inclined to follow it (Pichert & Katsikopoulos, 2008). It is assumed that investors use decision-support systems like robo-advisors because they want to relinquish a part of their responsibility (e.g. send orders to the market on their own or gather information about investments). On the other hand, they want to have the possibility to monitor their investment, which is a core feature of robo-advisors. Furthermore, they want to retain control or the feeling of control over their investment decisions. Nudging with a default option seems to be a fair compromise between these considerations and would nudge users of robo-advisory towards the optimal decision, without reducing the feeling of being in control.

These considerations suggests the following:

Hypothesis 1 (H1). *Preselecting the optimal option based on Bayesian rationality in the user-interface, will increase the decision-maker's tendency to choose that option, and hence reduce the decision-maker's decision inertia.*

5.3.2 Warning Message Nudge (H2)

Furthermore, this study proposes warning messages as a second nudge to reduce the tendency to rely on decision inertia. Warning messages are built on cognitive feedback theory (Balzer, Doherty, et al., 1989), which provides a framework to design feedback giving information about the cognitive system and the current decision-making related to the decision maker's own strategy. Compared to other feedback approaches, cognitive feedback is intended to encourage users of the information system to think more about their decisions and thereby prevent premature decisions (Sieck & Yates, 1997). If participants are subject to inertia, warning messages building on cognitive feedback should encourage biased decision-makers to reconsider their decision and, if necessary, to consider alternative options. Warning messages relying on cognitive feedback have been successfully used not only in decision support systems in other economic decision environments (see e.g., Xiao and Benbasat (2015) or Winkler and Moser (2016), but also in financial decision support systems to reduce biased decision-making (see e.g. Bhandari et al. (2008)). For instance, Sengupta et al. measured the performance of participants hired as virtual project managers in an economic market simulation (Sengupta & Abdel-Hamid, 1993). The market simulation consisted of a spontaneously changing environment and the participants' economic performance of the given task was measured. Considering the different feedback and project groups, Sengupta and Abdel-Hamid (1993) found that subjects induced with cognitive feedback performed significantly better than the other subjects with feed-forward or outcome feedback.

However, the effectiveness of warning messages depends mainly on how the messaging presented to the decision-maker (Xiao and Benbasat 2015). The complexity of the warning message, for example, tends to decrease fault correctability as well as benchmark efficiency among individuals (Kulhavy et al. 1985). For that purpose, this study relies on the evaluated design of warning messages as proposed by Bhandari et al. (2008).
Following this rationale, it is assumed that the warning messages building on cognitive feedback, may decrease the decision inertia of the users of the decision support system. Such a system simultaneously aims at choice accuracy and a more directive approach to influence an individual's understanding. Hence, it is postulated that:

Hypothesis 2 (H2). *Proving warning messages relying on cognitive feedback by the decision support system will decrease the decision-maker's decision inertia.*

5.4 Evaluate Digital Nudges to Overcome Decision Inertia

The current experimental investigation makes use of a between-subject, scenario-based laboratory experiment, where the behaviour of the participants is measured in the absence of external influences. The dependent variable, decision inertia, is defined as the tendency to repeat the previous decision regardless of the direct consequence, even if the consequence is clearly inferior to alternative options (Sautua, 2017; Alós-Ferrer et al., 2016). Following established decision inertia research, this study relies on a dual-choice belief-updating task (so-called dual-choice paradigm) to measure decision inertia (Alós-Ferrer et al., 2016; Achtziger & Alós-Ferrer, 2013; Charness & Levin, 2005) in the financial decision-making setting. In particular, decision inertia can be measured by the dual-choice paradigm by comparing errors of investors in choice sets when choice repletion is rational, and when it is not (Alós-Ferrer et al., 2016). For that purpose a simple market simulation was designed, where the participants had to invest with a robo-advisor. The robo-advisor itself has been implemented on the Brownie platform, allowing me to build on an established framework for experiments in information systems research (see also Section 4.2).

5.4.1 Method

In this task, participants were asked to virtually invest money with the robo-advisor in a market simulation, and successful outcomes were rewarded. Participants received 0.10 Euro (10:1 exchange rate) for each virtual monetary unit (MU) they had at the end of the experiment. The financial planning process in the robo-advisor had a market phase representing the main task of this experiment. During the market phase, participants were confronted with two subsequent investment decisions, repeated 60 times (120 rounds, which means 60 investments, and 60 rebalancing rounds), with the purpose to measure the decision inertia bias. In each round, the participants had to decide between two different investment strategies. The two strategies have different success rates (see Table 1), dependent on the market state.
However, the current market state is unknown to the participants. After every two subsequent

Table 18: The properties of the market with two different states, based on the dual-choice paradigm (see Alós-Ferrer et al. 2016; Charness and Levin 2005).

State of the Market	Strategy 1: Stocks	Strategy 2: Bonds
Bullish Market (p=.5)	Success Prob.: ● ● ● ● ○ ○ (4/6) Payoff: Win 1 MU, Loss 0 MU	Success Prob.: ● ● ○ ○ ○ ○ (2/6) Payoff: Win 1 MU, Loss 0 MU
Bearish Market (p=.5)	Success Prob.: ● ● ○ ○ ○ ○ (2/6) Payoff: Win 1 MU, Loss 0 MU	Success Prob.: ● ● ● ● ○ ○ (4/6) Payoff: Win 1 MU, Loss 0 MU

decisions (investment and rebalancing), the current market state is assigned randomly anew (based on the probabilities in Table 1). The task of the participants was to make a successful financial decision as often as possible, because the pay-off of the experiment depends on the outcome of their investments in each round. The participants can do that by using Bayesian updating to guess the state of the market, based on the feedback of the first investment decision.

If a participant exhibits decision inertia, a choice architect would expect them to stay with their first choice. If they chose the bond strategy for the first draw, they will choose the bond strategy for the second draw - regardless of the consequences of their decision. For example, let us assume that the participant chooses the bond strategy in their first draw. If the result is *no success*, it is more likely that the state of the market is *bullish*, relying on correct Bayesian updating (it is a 4/6 posterior probability that the market is bullish, and 2/6 posterior probability that the market is a bearish market). To maximize the chances in the second round (rebalancing decision), the participant ought to choose the stock strategy for the second draw. Based on the information from the previous draw, it can be said that staying with the first, inertia-driven, choice (bond strategy) is sub-optimal. Conversely, if the participant picked the bond strategy in the first round resulting in a success it is more likely that the state of the market is *bearish*. The participant ought to choose the bond strategy again for their second rebalancing decision. Optimal choice and inertia-driven choice are identical (choose bond strategy again).

Based on other decision inertia studies building on that paradigm (Alós-Ferrer et al., 2016; Charness & Levin, 2005), the occurrence of decision inertia is measured by way of comparing mean error rates of correct Bayesian updating, when choice repetition is suboptimal. The different screens of the experiment are illustrated in more detail in Figure 37.

5.4.2 Participants

The study was conducted in the Karlsruhe Decision and Design lab. 96 adult participants (male=55, female=55, other=0, age range=19-50, SD=3.60) took part, and were recruited with HRoot (Bock et al. 2014). They received a performance-based payment of 0.10 Euro for each successful investment, and were paid a fee of 3.0 Euro for answering the questionnaire. Mean payoff was 9.17 Euro (SD = 0.57). The whole experiment took approximately 45 minutes.

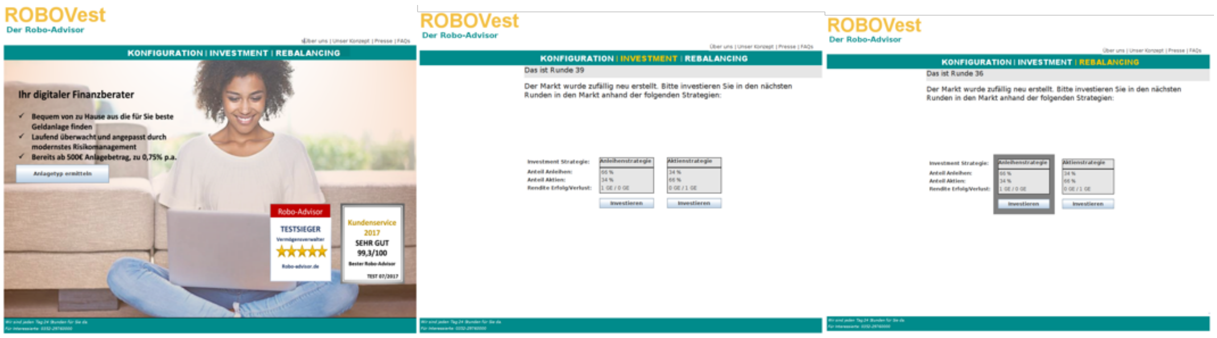


Figure 37: Selected screens of the distinct investment steps of the main experimental task, based on the dual-choice paradigm (Alós-Ferrer et al. 2016), and implemented in a general robo-advisory structure (see Section 3).

5.4.3 Procedure

To address the hypotheses, the following experiment was carried out, consisting of five steps (Figure 4). The steps are based on the Brownie guideline for conducting experimental research in information systems (see Section 4.2). In the first step, participants received instruction on the experiment and to participate in the experimental investigation had to consent in with a comprehension test to follow. These steps are necessary to make sure, that the participants are well-informed about the procedure and the circumstance of the market simulation and the investment game. In the next step, participants were induced to invest in the robo-advisor. Participants were then asked to invest the money in the provided robo-advisory solution. For that purpose they played multiple investment rounds (120 rounds, equals 60 investment and 60 subsequent rebalancing decisions). After every second round (rebalancing decision), the market state was reset randomly.

For the design and wording of the warning message, this study relied on Bhandari et al. (2008). When the user exhibited for the first time decision inertia, a warning message appeared (e.g., "You receive this feedback to help you to make your rebalancing decision. Currently, you just repeated your previous decision. However, the analysis suggests that the other strategy is more promising for you."). Following Bhandari et al., in this study the message appears only once; otherwise, the constant warning would cause an unwanted change in user behaviour, because it would have to be clicked away every time, and not because the user reconsidered his decision strategy.

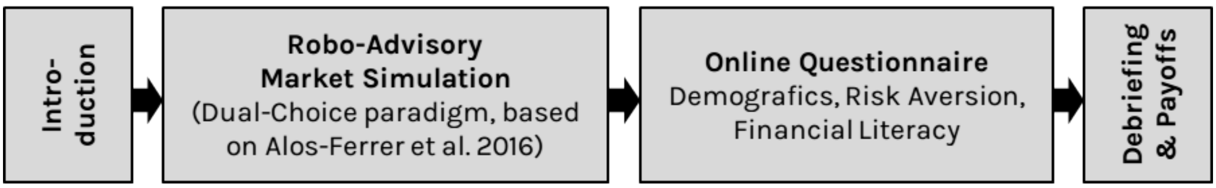


Figure 38: Procedure of the experimental investigation: in the market simulation participants are assigned randomly to one of the three conditions (between-subject design).

The design of the decision task and instructions were chosen in line with Alós-Ferrer et al. (2016), and Achtziger and Alós-Ferrer (2013). Furthermore, risk-aversion (Dohmen et al., 2011), financial literacy (Lusardi & Mitchell, 2007), gender and age were measured as control variables. Before the experimental study took place, a pre-test was conducted to make sure that I could reproduced decision inertia in the lab.

5.4.4 Results

Decision inertia was measured based on the dual-choice paradigm (see Section 4.2). In this paradigm, decision inertia is operationalized as the tendency of the participants to repeat a previous investment without correctly considering the new information. In the market parametrization this occurs, when the first investment is a loss, and the decision-maker repeats it without correct Bayesian updating. Consequently, the individual rates of suboptimal inertia-driven decisions are computed. They are then compared across the different treatments (see Figure 5) to investigate whether the nudges reduced participant's decision inertia. The mean rates of inertial decisions in the investments were 42.13 % (SD=28.7) in the control condition, 29.83 % (SD=25.71) in the default nudge treatment, and 27.38 % (SD=19.62) in the warning message treatment.

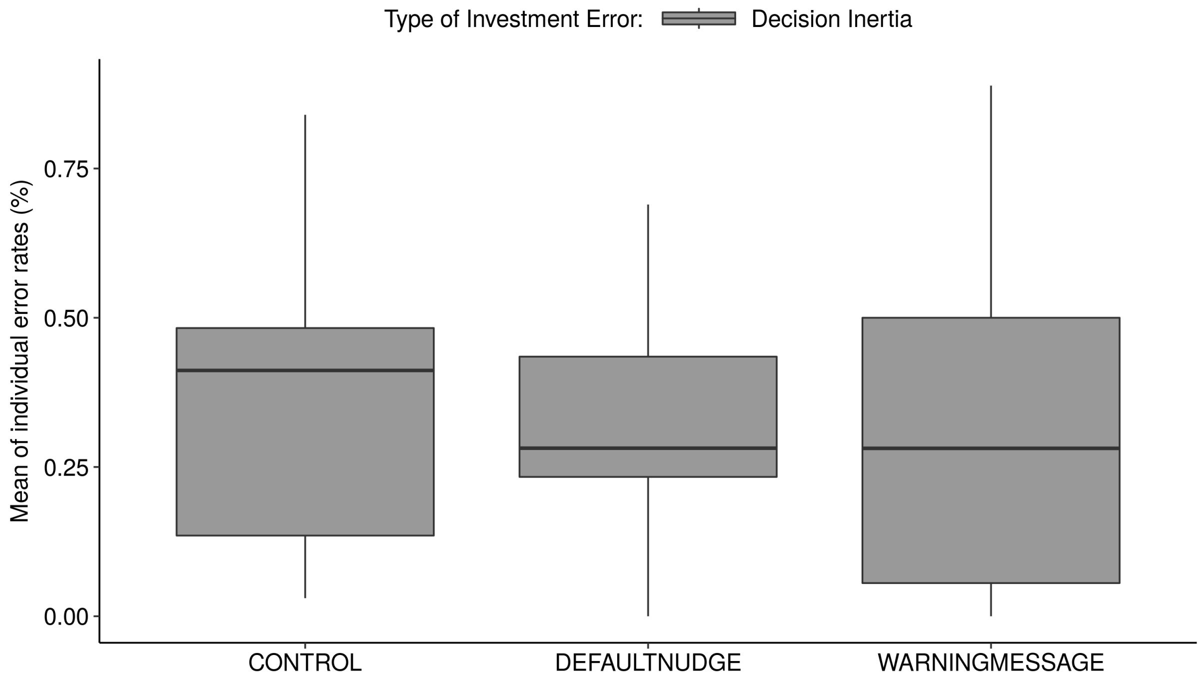


Figure 39: The effectiveness of financial support nudges: A comparison of the implemented nudges (defaults and warning messages) to reduce decision inertia in a decision support system, and the control group without nudges.

In order to test the two hypotheses (H1, H2), which state that digital nudges can influence the tendency to rely on decision inertia, the average inertia rate of the participants across the three treatments are compared against each other. In a first step, an ordinary least square regression that regresses the treatments (coded as dummy variables) on the decision inertia rates (Model 1) is used. As a robustness check, a model (Model 2) is computed that controls for potential confounds. In both models, a one-sided p-value was used to test the directed hypotheses.

All non-dummy variables (particularly decision inertia, financial literacy, risk aversion, and age) were z-standardized to obtain standardized beta regression coefficients. Furthermore, as a robustness check a one-way ANOVA on the treatment variable was conducted, suggesting similar results.

Table 2 shows the results for the two models. In both models, the treatments (default nudge, and warning message nudge) significantly influence decision inertia. Both coefficients of the dummy variables (Model 1) have a negative sign, which means that they have a negative influence on the dependent variable of decision inertia. When nudging participants with default messages, the results show that the decision inertia rate decreases by 0.59 standard deviations compared to the group without nudging.

Table 19: Linear regression on decision inertia rates in subsequent investments (1=decision inertia) across all rebalancing decisions.

Variable	Beta (SE)	P	Beta (SE)	P
		(1)		(2)
(Intercept)	0.3813	0.0421 *	0.50	0.4540
Default Nudge (1=True)	-0.5856	0.0102 *	-0.5798	0.009 **
Warning Message Nudge (1=True)	-0.4881	0.0276 *	-0.47056	0.0282 *
Financial Literacy	-	-	-0.2356	0.0217 *
Risk Aversion	-	-	0.0718	0.4676
Age	-	-	0.003	0.9133
Gender (1=Male)	-	-	-0.3392	0.0997 .

Number of obs./participants: 96; **Adjusted R-squared** = .04 (Model 1), .11 (Model 2)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Model 2, which includes the control variables (age, gender, financial literacy, risk aversion) supports this finding. The results provide evidence for a significant negative influence of nudges on decision-making. In addition, there was also a significant negative impact of financial literacy on decision inertia in the market simulation. As such, participants with better knowledge of properly making financial decisions also showed less decision inertia. However, the effects of the dummy variables on nudges remain significant, so users with high financial literacy can also benefit from the nudges. Another puzzling finding is a barely detectable statistically significant difference ($p<=.1$) in Model 2 suggesting that male participants showed a trend towards less inertia than did female participants. In a similar study, Charness and Levin reported a significant association between female participants and increased decision inertia (Charness & Levin, 2005). Another possible explanation for this finding could be gender role theory suggesting that social role models tend to make women remain passive, while men change strategies independently and dominantly. So far, there is only a nascent stream of research in financial services which partially explains financial choices with gender roles (see Hummel, Herbertz, and Mädche (2018)). Taking these findings together, it seems possible that decision inertia could be more common among women than men.

Based on the statistical analyses, the study therefore supports both hypotheses and it can be concluded that, compared to the control group, the implemented nudges have led to less financial decision inertia. Furthermore, a Wald-test to compare the effect of the nudges against each other was conducted. The test showed no significant results indicating that the effect for the default nudge does not significantly differ from the warning message nudges. Consequently, both nudges are equally elaborated design features to reduce financial decision inertia.

5.4.5 Discussion

This study aimed to shed light on the potential of financial planning tools like robo-advisors in reducing decision inertia by nudging users towards a better investment decision (in sense of Bayesian rationality). In particular, this study focuses on a specific facet of inertia: the tendency to repeat a previous choice, regardless of the consequences (Alós-Ferrer et al., 2016). It is hypothesized that decision inertia can be reduced by nudges in financial planning tools. The results of this study support the assumption that decision inertia can be mitigated by choice architecture design. Choice architecture is a theoretical framework guiding researcher in designing bias-sensitive systems. A consistent use of nudges derived from that theoretical framework, can help users to make better effortless and automatic decisions, and hence makes users less prone to specific biases. Furthermore, this study found that default nudges are more robust to overcome decision inertia compared to warning messages. The findings show that nudges can reduce financial decision inertia, however decision inertia is also linked to financial literacy and gender.

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The study contributes to the still nascent robo-advisor literature and research by expanding the understanding of choice architecture design to overcome decision inertia in financial planning tools. It is paramount to investigate nudges to overcome decision inertia to design information systems that can help decision-makers avoid falling into the trap of repeating unfavourable prior decisions. With this research design insights for existing decision support systems in various other contexts are given (e.g., decision inertia in health context or policy selection), which provides a foundation to implement adaptations that can better address this issue. The research applies to both users of information systems (and this is where the focus lies for the moment) and business decision-making, (e.g., in forecasting support systems).

However, the experimental study also has limitations worth mentioning. The study was conducted in a laboratory setting. This was necessary to reduce the effect of confounding variables, and to test whether decision inertia can be manipulated reliably and with high internal validity. However, it remains unclear whether the findings can be generalised to existing robo-advisory and financial planning tools. A practical evaluation of the nudges is necessary and would increase the validity of the design recommendations.

Another, more theoretical limitation is that this study builds on a choice architecture approach. However, the findings reveal further research needs from other perspectives: i) they indicate that increasing financial literacy (e.g. based on training) could be another approach to reduce decision inertia, and ii) that decision inertia is sensitive to gender differences. Firstly, since the purpose of this study was to develop and evaluate countermeasures for decision inertia, a next interesting step would be to further investigate gender-specific differences. Decision inertia seems to be more pronounced in women (see Model 1 in Table 19), so it seems promising to design and evaluate gender-specific nudges or training units. This would make it possible to address users of financial planning tools even more specifically and thus help them more efficiently.

Secondly, approaches from another theoretical perspective seem also to be promising. For instance, the significant influence of financial literacy, suggests that decision inertia (and probably other financial biases) can be partly explained by insufficient financial education. Building on that finding, financial education and training, seems to be a further promising pathway to reduce financial decision inertia. Furthermore, it would be interesting to benchmark the choice architecture approach and a financial training approach against each other. More research is required to identify further methods to overcome decision inertia.

Given these limitations, the study is intended to form a basis for future research at the intersection of behavioural economics and decision support systems. Based on the insights generated from the experiment, further examination of nudges to reduce decision inertia may be derived, and these insights may be used to develop further IT-based counter-measures. This study is one part of a research project designing adaptive decision support systems that detects situations in which the user is likely prone to biases such as decision inertia and reacts by changing those interface elements that likely exacerbate biases - for a specific user in a specific decision situation.

6 Conclusion

Prior work has documented the many-faceted difficulties of private investors in financial decision-making and the resulting need for financial decision support and robo-advisory (see e.g., Fisch, Laboure, et al. (2017); Looney and Hardin (2009)). In my thesis, I target this shortcoming aiming to help robo-advisor researchers and practitioners to design and develop robo-advisor systems (challenge 1), and to increase the advisory quality (challenge 2) by considering individual needs to overcome biased financial decision-making like decision inertia.

Considering the *first challenge*, I conducted a three cycled design science study to investigate general design requirements of robo-advisors. This study focused on a better understanding of user's decision-making in robo-advisors, and the interaction of these users with a robo-advisor (*Part I*). I used the findings to derive design recommendations for the general design of a robo-advisor solution. My house of robo-advisory design (see Figure 18) can be used by robo-advisor scholars as a mental guideline to design and develop basic robo-advisor solutions.

To target the *second challenge*, I focused on the advisor quality of robo-advisors. In a subsequent step, I selected an exemplar of a recent bias in economic decision-making, decision inertia (*Part II*), and investigated how advisor quality can be increased by helping users to overcome decision inertia in robo-advisory. Decision inertia is the tendency of decision-makers to repeat unsuccessful strategies regardless of the consequences (Alós-Ferrer et al., 2016; Dutt & Gonzalez, 2012). It can be responsible for suboptimal investment decisions, and it is generally accepted as a harmful bias in subsequent decision-making (Sautua, 2017; Alós-Ferrer et al., 2016; Erev & Haruvy, 2013). To overcome decision inertia, I first had to understand the driving forces behind this phenomenon. For that purpose, I conducted a series of experimental studies in the lab to distinguish and investigate cognitive and motivational drivers of decision inertia. Finally, I used the insights derived to implement two design features in a robo-advisor system (*Part III*). I tested the influence of these design features of decision inertia in a market simulation and showed their effectiveness in overcoming decision inertia.

6.1 Implications for Theory

This work contributes to the still-nascent stream of theoretical robo-advisor literature and research. The current robo-advisor research lacks theoretical guidelines describing and explaining how to design and develop robo-advisors. In particular, there are many biases in economic decision-making that remain not well understood, and it is yet unclear how robo-advisor systems (or financial decision support system in general) can target these shortcomings. In this thesis, I illustrated a theoretical guideline subsuming the most relevant requirements in robo-advisory design. This framework illustrates how the different requirements can be target by specific design decisions. Hence, it provides a first mental framework for the general design of robo-advisors and comparable financial decision support systems.

In my studies, I focused on a very recent bias in economic decision-making, decision inertia. Prior work has suggested that decision inertia is mainly driven by motivational factors. For instance, Alós-Ferrer et al. (2016) report the effects of preference for consistency on decision inertia (Alós-Ferrer et al., 2016). However, certain studies have produced opposite findings (Zhang et al., 2014; Pitz, 1969), while other studies have proposed further motivational factors like indecisiveness or decision avoidance as possible drivers of decision inertia (Sautua, 2017). Targeting the need to clarify these mixed results, I conducted a systematic literature review. My overview of the decision inertia literature illustrates the different conceptualizations of this phenomenon in judgement and decision-making research (see Section 4.1.1), neuro science research and related disciplines (see Section 4.1.2), and information system research (see Section 4.1.3). Furthermore, this overview demonstrates that decision inertia has many implications, and suggests that it is a multi-determined bias (cognitivly and motivationally driven), which could explain the mixed results in previous studies. Based on my literature review, I proposed that cognitive processes like an individual's evidence threshold and Bayesian probability updating capabilities may play a relevant role in explaining decision inertia in addition to motivational factors. Finally, I integrate the findings of my studies by distinguishing between the most relevant motivational and cognitive drivers (see Section 4.6). Most notably, this is the first study to my knowledge that compares the interplay of cognitive and motivational drivers of decision inertia.

Last but not least, my experiments suggest that the motivational factors are not as stable as has been assumed. The results illustrated that only action orientation is consistently associated with decision inertia. Other motivational factors like preference for consistency or indecisiveness showed no significant associations. Furthermore, cognitive differences in evidence thresholds and capabilities in Bayesian updating affected the suboptimal behaviour rate in general but not decision inertia specifically. Combining this observation with the significant influence of action orientation, my findings suggest that decision inertia could be the result of an interplay of loss-evidence considerations. In particular, decision-makers rely on decision inertia, because they want not to engage too much with negative events and make faster and riskier decisions.

Further research could investigate these relationships in more detail. For instance, there are further possible individual characteristics that could act as drivers of decision inertia. These findings could be used as possible indicators of individuals sensitive to decision inertia. If an individual is sensitive, it could be supported by trainings and warnings, and hence help the individual to overcome decision inertia before it can result in negative consequences.

However, some limitations are worth noting in this context. Although my hypotheses were supported statistically, there remains a need to investigate whether decision inertia is primarily context-induced or is rather a stable personality trait that does not change over a wide range of time and decision situations. This investigation is necessary to design and develop further counter-methods against decision inertia. Future work should therefore investigate whether decision inertia phenomena are stable over time and whether they contribute to other choice avoidance phenomena in economic decision-making, such as inaction inertia, omission bias or decision avoidance in general.

Moreover, I focused on decision inertia only as an example of biased financial decision-making. So far, the judgement and decision-making literature provides evidence of many other biases in financial decision making (e.g., overconfidence, household bias, home bias to name a few); see also Benartzi and Thaler (2007); Bazerman et al. (2002)). Future robo-advisor research, should bear these other biases in mind trying to find other approaches to reduce the other common biases to help users make better investment decisions.

6.2 Implications for Practice

My studies do not contribute only to the theoretical understanding of decision-making, and the inertia phenomena in robo-advisory, but also illuminate explicit design interventions to overcome these phenomena. An ever greater number of decisions are made in digital environments or are at least supported by digital technology. From an information system design perspective, this study provides insights which can be used in other information systems where decision inertia occurs.

The proposed nudges, could help overcome decision inertia in various other setting; for instance, in business decision-making scenarios. Most managers have to make various subsequent decisions, and it seems reasonable that in management decision-making, decision inertia can have a negative influence. Designers of management information systems, or decision support systems in general, must consider not pushing their users accidentally into the decision inertia bias. Using the insights from this work, they now have two design features at hand to reduce decision inertia in such information systems.

My results provide the foundation for designing countervailing measures. Take, for instance, a recommender system user-interface. A user who has high action-orientation induced by a win framing of the user interface (for instance, by messages that describe the pleasures of the recommendation) may be pushed accidentally into decision inertia. A user who is presented with a first default option, on the other hand, may experience less decision inertia but suffer increased errors in divergence and convergence situations. Highly action-orientated decision makers could be detected, through a survey given prior to decision-making and faced with a special warning if they tend to repeat previous decisions (even if such a survey is probably not feasible in all situations).

In particular, further work in the research stream of adaptive information systems seems to offer a promising pathway to continue this work (see Figure 2), and to develop adaptive information systems that detect decision inertia (and other biases) when they occur. In a subsequent step, they could de-bias users by nudging them and helping them overcome biased decision-making.

However, one relevant limitation of this work is that I proposed two design features to overcome decision inertia. However, it seems likely that other nudges could also help to reduce decision inertia in financial decision-making. I decided on these nudges based on their effect size, and fit with the identified drivers, and because they have been successfully applied in comparable problems. Nevertheless, the choice architecture toolbox (Johnson et al., 2012) contains many other nudges to overcome biased decision-making. Practitioners building robo-advisor prototypes could try to identify and evaluate other suitable nudges for their feasibility

to reduce decision inertia.
Furthermore, the explanatory power of the findings and recommendations of my studies could be increased through practical evaluation. Future researchers and practitioners should test the findings in a real-life robo-advisory solutions with real users. It is unlikely, but nonetheless possible that in real-life decision-making, nudges do not have not have the same positive effect on overcoming decision inertia in financial decision-making.
Finally, my results show that robo-advisors can help investors overcome decision biases. Unexperienced investors, in particular, profit from robo-advisory support in financial decision-making. Considering that robo-advisors are relatively inexpensive and easily accessible for all kinds of users, future research into how robo-advice can be adapted to give more effective feedback and support during the investment process seems very promising with regards to improving financial decision-making.

A Scales and Questionnaires

Overview of the used scales and questionnaires used in the studies.

Think Aloud Interview Guideline

Table 20: Interview guideline for the think aloud study in the design science study.

ID	Original Item	Dimension
1	*Hast Du den Eindruck, dass Du alle für Dich wichtigen Informationen über die Firma und das Angebot erhalten und verstanden haben? Wenn nein, was fehlt oder ist nicht verständlich?*	Effectiveness, Efficency, Transparency (Cost, Process, Information)
2	*Fühlst Du dich nun in der Lage, eine Entscheidung für oder gegen eine Geldanlage bei dieser Firma zu treffen? Wenn nein, weshalb?*	Effectiveness, Transparency (Information), Understanding
3	*Wie findest Du das beschriebene Angebot?*	Satisfaction, Efficency
4	*Welche Informationen haben Dich negativ überrascht?*	Effectiviness, Expectation Conformity, Anticipation
5	*Welche Informationen haben Dich positiv überrascht?*	Effectiviness, Expectation Conformity, Anticipation
6	*Wie findest Du die Bedienung*	Satisfaction, Ease of Navigation, Controllability, Structural Consistency, Error Tollerance
7	*Fandst Du die Navigation selbsterklärend / übersichtlich? Am Ende mehr als am Anfang? Wenn nein, an welchen Stellen?*	Ease of Navigation, Anticipation, Error Tollerance, Structural Consistency, Transparency (Process)
8	*Was fandst Du verwirrend oder widersprüchlich?*	Expectation Conformity, Transparency (Process, Information)
9	*Wie hast Du Dich auf der Startseite zurecht gefunden? Fandst Du sie übersichtlich?*	Efficency, Ease of Navigation, Controllability, Transparency (Process, Information)

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Table 20 – *Continued from previous page*

10	*Welche Informationen hättest Du auf der Startseite nicht gebraucht? Welche hast Du vermisst?*	Efficency, Ease of Navigation, Transparency (Cost, Process, Information)
11	*Kannst du mit dem Angebot aktive und passive Fonds etwas anfangen? Was ist aus deiner Sicht der Unterschied zwischen aktiv und passiv gemanagten Fonds?*	Understanding, Transparency (Information)
12	*Vertraust du der Empfehlung?*	Satisfaction, Transparency (Cost, Process, Information)
13	*Könntest Du Dich jetzt für ein Portfolio entscheiden? Wenn nein, würdest Du es speichern und später noch einmal darüber nachdenken?*	Effectiviness, Understanding, Transparency (Cost, Process, Information)
14	*Wie findest du die Lösung der Website, Produkte auf diese Weise anzubieten?*	Satisfaction, Understanding, Transparency (Cost, Process, Information)
15	*Vertraust du der Website und dem Angebot? Warum würdest du dem Robo-Advisor vertrauen?*	Transparency (Cost, Process, Information)
16	*Was schränkt dein Vertrauen gegenüber dem Robo-Advisor ein, oder verunsichert dich?*	Transparency (Cost, Process, Information), Understanding, Error Tollerance

Indecisiveness Scale

Table 21: Indecisiveness questionnaire from Spunt et al. (2009) to measure individual's disposition to perceive difficulties when making a decision, and its preference for decision avoidance in decision-making.

Original Item	German Translation	Dimension
Once I make a decision, I feel fairly confident that it is a good one	*Sobald ich eine Entscheidung getroffen habe, bin ich ziemlich sicher, dass es eine gute ist*	Aversive Subscale, reversed item
Once I make a decision, I stop worrying about it	*Sobald ich eine Entscheidung getroffen habe, höre ich auf, mir darüber Gedanken zu machen*	Aversive subscale, reversed item
I become anxious when making a decision	*Ich werde ängstlich, wenn ich eine Entscheidung treffe*	Aversive subscale
I often worry about making the wrong choice	*Ich mache mir oft Sorgen, die falsche Wahl zu treffen*	Aversive subscale
After I have chosen or decided something, I often believe I've made the wrong choice or decision	*Nachdem ich etwas ausgewählt oder entschieden habe, glaube ich oft, dass ich die falsche Entscheidung getroffen habe*	Aversive subscale
I try to put off making decisions	*Ich versuche, Entscheidungen hinauszuzögern*	Avoidant subscale
I always know exactly what I want	*Ich weiß immer genau, was ich will*	Avoidant subscale, reversed item
I find it easy to make decisions	*Ich finde es einfach, Entscheidungen zu treffen*	Avoidant subscale, reversed item
I like to be in a position to make decisions	*Ich bin gerne in der Lage, Entscheidungen zu treffen*	Avoidant subscale, reversed item
I usually make decisions quickly	*Normalerweise treffe ich Entscheidungen schnell*	Avoidant subscale, reversed item
It seems that deciding on the most trivial thing takes me a long time	*Es scheint, dass die Entscheidung über die trivialste Sache eine lange Zeit dauert*	Avoidant subscale

Risk Attitude Scale 1

Description: *Auf Ihrem Entscheidungsblatt sind auf der linken Seite zehn Entscheidungen aufgelistet. Jede Entscheidung besteht aus der Wahl zwischen „Option A“ und „Option B“. Insgesamt müssen Sie zehn Entscheidungen treffen und diese in der letzten Spalte eintragen. Am Ende des Experiments wird jedoch nur genau eine Ihrer Entscheidungen ausgewählt, die dann ausgezahlt wird. Das auszahlungsrelevante Ergebnis wird mit einem zehnseitigen Würfel bestimmt; die Seiten sind nummeriert von 0 – 9 (die Zahl „0“ soll die „10“ repräsentieren.) Nachdem Sie Ihre zehn Entscheidungen getroffen haben wird der Würfel zunächst geworfen, um zu bestimmen, welche der zehn Entscheidungen für die Auszahlungsberechnung herangezogen wird. Danach wird der Würfel noch einmal geworfen, um die Auszahlung in Option A oder B zu bestimmen. Sehen Sie sich nun die erste Reihe an. Option A bringt Ihnen 2,00 Euro falls der zehnseitige Würfel 1 zeigt und 1,60 Euro falls der Würfel 2-10 (0) zeigt. Mit Option B können Sie 3,85 Euro gewinnen falls der Würfel 1 zeigt und 10 Cent falls der Würfel 2-10 (0) zeigt. Die anderen Entscheidungen sind ähnlich, wobei in jeder Reihe bei beiden Optionen die Chancen, die höhere Auszahlung zu erreichen, steigen. Schließlich, bei der zehnten Entscheidung (in der letzten Reihe), wird der Würfel nicht benötigt, da jede Option die höhere Auszahlung garantiert. Sie können Ihre Entscheidung in einer beliebigen Reihenfolge treffen und auch nachträglich noch ändern. Bei der Auszahlung haben Sie dann die Möglichkeit, zweimal zu würfeln, um die auszahlungsrelevante Entscheidung zu bestimmen. Ihr Gewinn (in Euro) bei dieser Entscheidung wird zu Ihren vorherigen Gewinnen hinzuaddiert und die Summe dann ausgezahlt. Haben Sie noch Fragen? Sie können nun beginnen Ihre Entscheidungen zu treffen. Bitte sprechen Sie währenddessen mit Niemandem; wenn Sie eine Frage haben, heben Sie bitte einfach Ihre Hand.*

Table 22: Risk attitude questionnaire from Holt and Laury (2005) to measure individual's disposition to risk in economic decision-making.

Option A	**Option B**	**Your Choice**
1/10 Chance auf €2.00; 9/10 Chance auf €1.60	1/10 Chance auf €3.85; 9/10 Chance auf €0.10	
2/10 Chance auf €2.00; 8/10 Chance auf €1.60	2/10 Chance auf €3.85; 8/10 Chance auf €0.10	
3/10 Chance auf €2.00; 7/10 Chance auf €1.60	3/10 Chance auf €3.85; 7/10 Chance auf €0.10	
4/10 Chance auf €2.00; 6/10 Chance auf €1.60	4/10 Chance auf €3.85; 6/10 Chance auf €0.10	
5/10 Chance auf €2.00; 5/10 Chance auf €1.60	5/10 Chance auf €3.85; 5/10 Chance auf €0.10	

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Table 22 – *Continued from previous page*

6/10 Chance auf €2.00; 4/10 Chance auf €1.60	6/10 Chance auf €3.85; 4/10 Chance auf €0.10
7/10 Chance auf €2.00; 3/10 Chance auf €1.60	7/10 Chance auf €3.85; 3/10 Chance auf €0.10
8/10 Chance auf €2.00; 2/10 Chance auf €1.60	8/10 Chance auf €3.85; 2/10 Chance auf €0.10
9/10 Chance auf €2.00; 1/10 Chance auf €1.60	9/10 Chance auf €3.85; 1/10 Chance auf €0.10
10/10 Chance auf €2.00; 0/10 Chance auf €1.60	10/10 Chance auf €3.85; 0/10 Chance auf €0.10

Preference for Consistency Scale - short

Table 23: German short version Collani and Blank (2013) of the questionnaire from Cialdini et al. (1995) to measure individual's preference for consistency.

Original Item	Dimension
Es ist mir wichtig, dass meine Handlungen im Einklang mit meinen Überzeugungen stehen	Internal consistency
Ich finde es wichtig, dass Leute, die mich kennen, mein Verhalten vorhersagen können	Public consistency
Ich fühle mich unwohl, wenn ich zwei Überzeugungen besitze, die nicht zusammenpassen	Internal consistency
Es ist mir nicht wichtig, ob ich auf andere widersprüchlich wirke	Public consistency, reversed item
Es macht mir nichts aus, wenn meine Handlungen miteinander unvereinbar sind	Internal consistency, reversed item
Ich lege keinen Wert darauf, dass meine engen Freunde berechenbar sind	Consistency of others, reversed item
Ich mag keine Menschen, die dauernd ihre Meinung ändern	Consistency of others

Preference for Consistency Scale - full

Table 24: German long version of the questionnaire from Cialdini et al. (1995) to measure individual's preference for consistency.

Original Item	**German Translation**	**Dimension**
I prefer to be around people whose reactions I can anticipate	*Ich habe lieber Personen um mich, deren Reaktionen ich vorhersagen kann*	Consistency of others
It is important to me that my actions are consistent with my beliefs.	*Ich finde es wichtig, dass meine Handlungen im Einklang mit meinen Überzeugungen stehen*	Internal consistency
Even if my attitudes and actions seemed consistent with one another to me, it would bother me if they did not seem consistent in the eyes of others	*Selbst wenn für mich meine Handlungen im Einklang mit meinen Überzeugungen stehen, würde es mich stören, wenn sie in den Augen der Anderen nicht im Einklang stehen.*	Public consistency
It is important to me that those who know me can predict what I will do.	*Ich finde es wichtig, dass Leute, die mich kennen, mein Verhalten vorhersagen können.*	Public consistency
I want to be described by others as a stable, predictable person.	*Ich möchte von Anderen gerne als stabile und berechenbare Person beschrieben werden*	Public consistency
Admirable people are consistent and predictable	*Bewundernswerte Leute sind konsistent und berechenbar.*	Consistency of others
The appearance of consistency is an important part of the image I present to the world.	*Konsistent zu wirken ist ein wichtiger Teil des Bildes, das ich der Welt präsentiere.*	Public consistency
It bothers me when someone I depend on is unpredictable	*Es stört mich, wenn ich von jemandem abhängig bin, der unberechenbar ist.*	Consistency of others
I don't like to appear as if I am inconsistent	*Ich mag es nicht, inkonsistent zu wirken.*	Internal consistency
I get uncomfortable when I find my behavior contradicts my beliefs	*Mir wird unwohl, wenn meine Handlungen meinen Überzeugungen widersprechen.*	Internal consistency

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Table 24 – *Continued from previous page*

An important requirement for any friend of mine is personal consistency	*Eine wichtige Voraussetzung um zu meinen Freunden zu gehören ist persönliche Konsistenz.*	Consistency of others
I typically prefer to do things the same way	*Normalerweise ziehe ich es vor, die Dinge auf die gleiche Art und Weise zu machen.*	Internal consistency
I dislike people who are constantly changing their opinions	*Ich mag keine Menschen, die dauernd ihre Meinung ändern.*	Consistency of others
I want my close friends to be predictable	*Ich lege Wert darauf, dass meine engen Freunde berechenbar sind.*	Consistency of others
It is important to me that others view me as a stable person	*Mir ist es wichtig, dass mich Andere als stabile Person wahrnehmen.*	Public consistency
I make an effort to appear consistent to others	*Ich strenge mich an, auf Andere konsistent zu wirken.*	Internal consistency
I'm uncomfortable holding two beliefs that are inconsistent	*Ich fühle mich unwohl, wenn ich zwei Überzeugungen besitze, die nicht zusammenpassen.*	Internal consistency
It doesn't bother me much if my actions are inconsistent	*Es stört mich nicht sonderlich, wenn meine Handlungen nicht zueinander passen.*	Internal consistency, reversed item

Action Control Scale

Table 25: HAKEMP-24 (Action Control Scale : ACS) of Kuhl (1994b) to measure individual's disposition to action- or state-orientation.

ID	Original Item	German Translation	Dimension
1	*When I have lost something valuable and can't find it anywhere:*	*Wenn ich etwas Wertvolles verloren habe und es nirgendwo finden kann:*	
A	*I have a hard time concentrating on anything else.*	*Fällt es mir schwer mich auf etwas Anderes zu konzentrieren*	Failure-related preoccupation
B	*I don't dwell on it.*	*Beharre ich nicht darauf es zu finden.*	Failure-related action orientation
2	*When I know I must finish something soon:*	*Wenn ich weiß, dass ich bald etwas fertigstellen muss:*	
A	*I have to push myself to get started.*	*Muss ich mir einen Anstoß geben um anzufangen.*	Decision-related hesitation
B	*I find it easy to get it done and over with.*	*Finde ich es einfach es fertigzustellen.*	Decision-related action orientation
3	*When Ive worked for weeks on one project and then everything goes completely wrong:*	*Wenn ich mehrere Wochen an einem Projekt gearbeitet habe und dann alles völlig schiefläuft:*	
A	*It takes me a long time to get over it.*	*Brauche ich eine lange Zeit um darüber hinweg zu kommen.*	Failure-related preoccupation
B	*It bothers me for a while, but then I dont think about it anymore.*	*Ärgert das mich eine Weile lang, aber dann denke ich nicht mehr darüber nach.*	Failure-related action orientation
4	*When I have lost something valuable and can't find it anywhere*	*Wenn ich nichts Besonderes zu tun habe und mir langweilig wird:*	
A	*I have trouble getting up enough energy to do anything at all.*	*Fällt es mir schwer ausreichend Energie aufzubringen um überhaupt etwas zu tun.*	Decision-related hesitation
B	*I quickly find something to do.*	*Fällt mir schnell ein was ich tun kann.*	Decision-related action orientation
5	*When Im in a competition and lose every time:*	*Wenn ich in einem Wettbewerb bin und jedes Mal verliere:*	

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Table 25 – *Continued from previous page*

A	*I can soon put losing out of my mind.*	*Bekomme ich den Gedanken ans Verlieren schnell aus meinem Kopf.*	Failure-related action orientation
B	*The thought that I lost keeps running through my mind.*	*Geht mir der Gedanke ans Verlieren ständig durch den Kopf.*	Failure-related preoccupation
6	*When I am getting ready to tackle a difficult problem:*	*Wenn ich mich vorbereite ein schwieriges Problem anzugehen:*	
A	*It feels like I am facing a big mountain that I dont think I can climb.*	*Fühlt es sich so an, als ob ich vor einem großen Berg stehe, den ich glaube nicht besteigen zu können.*	Decision-related hesitation
B	*I look for a way that the problem can be approached in a suitable manner.*	*Suche ich nach einer Art und Weise, wie ich das Problem angemessen angehen kann.*	Decision-related action orientation
7	*If I had just bought a new piece of equipment (for example, a laptop) and it accidentally fell on the floor and was damaged beyond repair:*	*Falls ich gerade ein neues Arbeitsgerät (z.B. einen Laptop) gekauft habe und es mir aus Versehen auf den Boden gefallen ist und es so kaputtgegangen ist, dass man es nicht mehr reparieren kann:*	
A	*I would get over it quickly.*	*Würde ich schnell darüber hinwegkommen.*	Failure-related action orientation
B	*It would take me a while to get over it.*	*Würde ich eine Zeit lange brauchen um darüber hinwegzukommen.*	Failure-related preoccupation
8	*When I have to solve a difficult problem:*	*Wenn ich ein schwieriges Problem zu lösen habe:*	
A	*I usually get on it right away.*	*Fange ich normalerweise direkt damit an.*	Decision-related action orientation
B	*Other things go through my mind before I can get down to working on the problem.*	*Gehen mir erst andere Dinge durch den Kopf bevor ich anfangen kann mich mit dem eigentlichen Problem zu beschäftigen.*	Decision-related hesitation

Continued on next page

Table 25 – *Continued from previous page*

9	*When I have to talk to someone about something important and, repeatedly, cant find her/him at home:*	*Wenn ich mit jemanden über etwas Wichtiges reden will und ich sie/ihn öfters nicht zu Hause auffinden kann:*	
A	*I cant stop thinking about it, even while Im doing something else.*	*Kann ich nicht aufhören darüber nachzudenken auch wenn ich gerade etwas Anderes tue.*	Failure-related preoccupation
B	*I easily forget about it until I can see the person again.*	*Fällt es mir einfach es abzuhaken bis ich die Person wiedersehen kann.*	Failure-related action orientation
10	*When I have to make up my mind about what I am going to do when I get some unexpected free time:*	*Wenn ich unerwartete Freizeit habe und mich entscheiden muss was ich tue:*	
A	*It takes me a while to decide what I should do.*	*Brauche ich eine Weile um zu entscheiden was ich tue.*	Decision-related hesitation
B	*I can usually decide on something to do without having to think it over very much.*	*Entscheide ich mich normalerweise etwas zu tun ohne groß darüber nachdenken zu müssen.*	Decision-related action orientation
11	*When Ive bought a lot of stuff at a store and realize when I get home that I paid too much - but I cant get my money back:*	*Wenn ich viel in einem Laden eingekauft habe und zu Hause erst bemerkt habe, dass ich zu viel bezahlt habe aber mein Geld nicht zurückbekommen kann:*	
A	*I cant concentrate on anything else.*	*Kann ich mich auf nichts Anderes konzentrieren.*	Failure-related preoccupation
B	*I easily forget about it.*	*Fällt es mir einfach es abzuhaken.*	Failure-related action orientation
12	*When I have work to do at home:*	*Wenn ich Arbeit zu Hause erledigen muss:*	
A	*It is often hard for me to get started.*	*Finde ich es oft schwer damit anzufangen.*	Decision-related hesitation
B	*I usually get started right away.*	*Fange ich normalerweise gleich damit an.*	Decision-related action orientation

Continued on next page

Table 25 – *Continued from previous page*

13	*When I am told that my work has been completely unsatisfactory:*	*Wenn mir gesagt wird, dass meine Arbeit völlig unbefriedigend erledigt wurde:*	
A	*I dont let it bother me for too long.*	*Lass ich mich davon nicht lange stören.*	Failure-related action orientation
B	*I feel paralyzed.*	*Fühle ich mich wie gelähmt.*	Failure-related preoccupation
14	*When I have a lot of important things to do:*	*Wenn ich eine Menge wichtiger Sachen zu erledigen habe:*	
A	*I often dont know where to begin.*	*Weiß ich oft nicht wo ich beginnen soll.*	Decision-related hesitation
B	*I find it easy to make a plan and stick with it.*	*Fällt es mir einfach einen Plan zu machen und mich daran zu halten.*	Decision-related action orientation
15	*When Im stuck in traffic and miss an important appointment:*	*Wenn ich im Stau stehe und einen wichtigen Termin verpasse:*	
A	*At first, its difficult for me to start doing anything else at all.*	*Finde ich es erstmal schwierig mit irgendetwas Anderem anzufangen.*	Failure-related preoccupation
B	*I quickly forget about it and focus on something else.*	*Fällt es mir einfach nicht mehr weiter drüber nachzudenken und ich kann mich auf etwas Anderes fokussieren.*	Failure-related action orientation
16	*When there are two things that I really want to do, but I cant do both of them:*	*Wenn es zwei Sachen gibt, die ich wirklich machen will, aber nicht beide machen kann:*	
A	*I quickly begin one thing and forget about the other.*	*Fange ich schnell mit einer Sache an und hake die Andere ab.*	Decision-related action orientation
B	*Its not easy for me to put the thing that I couldnt do out of my mind.*	*Fällt es mir nicht einfach, die nicht gemachte Sache aus dem Kopf zu bekommen.*	Decision-related hesitation
17	*When something is very important to me, but I cant seem to get it right:*	*Wenn mir etwas sehr wichtig ist, es aber so aussieht als ob ich es nicht richtig hinbekomme:*	
A	*I gradually lose heart.*	*Verliere ich nach und nach den Mut.*	Failure-related preoccupation

Continued on next page

Table 25 – *Continued from previous page*

B	*I just forget about it and go do something else.*	*Hake ich es schnell ab und mache etwas Anderes.*	Failure-related action orientation
18	*When I have to carry out an important but unpleasant task:*	*Wenn ich eine wichtige aber unangenehme Aufgabe mache muss:*	
A	*I do it and get it over with.*	*Mache ich sie und bringe sie hinter mich.*	Decision-related action orientation
B	*It can take a while before I can bring myself to do it.*	*Brauche ich eine Weile bevor ich mich motivieren kann sie zu machen.*	Decision-related hesitation
19	*When something really gets me down:*	*Wenn mich etwas wirklich deprimiert:*	
A	*I have trouble doing anything at all.*	*Habe ich Probleme überhaupt etwas zu machen.*	Failure-related preoccupation
B	*I find it easy to distract myself by doing other things.*	*Finde ich es einfach mich abzulenken, indem ich andere Sachen mache.*	Failure-related action orientation
20	*When I am facing a big project that has to be done:*	*Wenn ich ein großes Projekt habe das erledigt werden muss:*	
A	*I often spend too long thinking about where I should begin.*	*Verbringe ich oft zu lange damit nachzudenken, womit ich anfangen soll.*	Decision-related hesitation
B	*I dont have any problems getting started.*	*Habe ich keinerlei Probleme damit anzufangen.*	Decision-related action orientation
21	*When several things go wrong on the same day:*	*Wenn an einem Tag mehrere Dinge schieflaufen:*	
A	*I don't know how to deal with it.*	*Weiß ich nicht wie ich damit umgehen soll.*	Failure-related preoccupation
B	*I just keep on going as though nothing had happened.*	*Mache ich einfach so weiter als ob nichts passiert wäre.*	Failure-related action orientation
22	*When I have a boring assignment:*	*Wenn ich eine langweilige Aufgabe habe:*	
A	*I usually dont have any problem getting through it.*	*Habe ich normalerweise keine Probleme diese zu erledigen.*	Decision-related action orientation
B	*I sometimes just cant get moving on it.*	*Kann ich mich manchmal einfach gar nicht dafür motivieren.*	Decision-related hesitation

Continued on next page

Table 25 – *Continued from previous page*

23	*When I have put all my effort into doing a really good job on something and the whole thing doesnt work out:*	*Wenn ich meine ganze Kraft reingesteckt habe um ein wirklich gutes Ergebnis zu erzielen und die gesamte Sache nicht funktioniert:*	
A	*I dont have too much difficulty starting something else.*	*Habe ich keine Probleme damit etwas Anderes anzufangen.*	Failure-related action orientation
B	*I have trouble doing anything else at all.*	*Habe ich Probleme irgendetwas anderes zu machen.*	Failure-related preoccupation
24	*When I have an obligation to do something that is boring and uninteresting:*	*Wenn ich etwas tun muss das langweilig und uninteressant ist:*	
A	*I do it and get it over with.*	*Mache ich es und bringe es hinter mich.*	Decision-related action orientation
B	*It usually takes a while before I get around to doing it.*	*Brauche ich normalerweise eine Weile bis ich sie mache.*	Decision-related hesitation

Financial Literacy Scale

Table 26: Financial Literacy questionnaire from Lusardi and Mitchell (2007) to measure individual's literacy in the financial domain. German translation adapted from L. Hansen et al. (2015).

Original Item	**German Translation**
Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? *(1) More than $102* *(2) Exactly $102* *(3) Less than $102* *(4) Don't know*	*Angenommen, Sie haben 100, - € Guthaben auf Ihrem Sparkonto. Dieses Guthaben wird mit 2 % pro Jahr verzinst, und Sie lassen es 5 Jahre auf diesem Konto. Was meinen Sie: Wie viel Guthaben weist Ihr Sparkonto nach 5 Jahren auf?* *(1) Mehr als 102 Euro* *(2) Genau 102 Euro* *(3) Weniger als 102 Euro* *(4) Weiß ich nicht*
Imagine that the interest rate on your savings account was 1 % per year and inflation was 2% per year. After 1 year, with the money in this account, would you be able to buy... *(1) More than today* *(2) Exactly the same as today* *(3) Less than today* *(4) Don't know*	*Angenommen, die Verzinsung Ihres Sparkontos beträgt 1% pro Jahr und die Inflationsrate beträgt 2% pro Jahr. Was glauben Sie: Werden Sie nach einem Jahr mit dem Guthaben des Sparkontos genauso viel, mehr oder weniger als heute kaufen können?* *(1) Mehr* *(2) Genauso viel* *(3) Weniger* *(4) Weiß ich nicht*
If the interest rate falls, what should happen to bond prices? *(1) Rise* *(2) Fall* *(3) Stay the same* *(4) None of the above* *(5) Don't know*	*Was geschieht bei steigenden Marktzinsen mit dem Preis einer festverzinslichen Anleihe?* *(1) Der Preis steigt* *(2) Der Preis fällt* *(3) Der Preis verändert sich nicht* *(4) Es gibt keinen Zusammenhang zwischen dem Preis einer festverzinslichen Anleihe und den Zinsen* *(5) Weiß ich nicht*

Risk Attitude Scale 2

Table 27: Risk aversion questionnaire from Dohmen et al. (2011) to measure individual's risk aversion in decision-making.

Original Item	German Translation
How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'	*Wie schätzen Sie sich persönlich ein: Sind Sie im allgemeinen ein risikobereiter Mensch oder versuchen Sie, Risiken zu vermeiden? Bitte kreuzen Sie ein Kästchen auf der Skala an, wobei der Wert 0 bedeutet: "gar nicht risikobereit" und der Wert 10: "Sehr risikobereit". Mit den Werten dazwischen können Sie Ihre Einschätzung abstufen*

B Participant Instructions

Friendly User Study - General Instructions

Hallo,
vielen Dank, dass Sie sich bereit erklärt haben, an unserer Studie teilzunehmen. In unserer Studie untersuchen wir die Oberfläche einer Website zur privaten Finanzplanung bezüglich Ihrer Nutzerfreundlichkeit. Wir werden mit Ihnen die Methode des lauten Denkens anwenden. Dazu bitten wir Sie, während Sie sich auf der Website bewegen, Ihre Gedanken kontinuierlich zu verbalisieren. Sprechen Sie bitte frei aus, was Sie gerade tun, was Sie sehen, empfinden und was Ihnen auffällt. Es gibt bei dieser Methode keine richtigen oder falschen Antworten.
Während der Studie begleitet Sie ein Studienleiter; also ich. Ich werde Ihnen hin und wieder Fragen stellen und stehe Ihnen natürlich auch für eventuelle Fragen Ihrerseits zur Verfügung. Meine Rolle ist aber nur eine begleitende; bitte bewegen Sie sich frei durch die Website. Das Experiment wird etwa 40 Minuten dauern. Ich möchte Sie bitten Ihre Eindrücke und Gedanken laut auszusprechen. Nach 40 Minuten habe ich noch ein paar abschließende Fragen sowie zwei Fragebogen vorbereitet.
Wenn Sie keine weiteren Fragen mehr haben, werde ich als Experimentator das Aufnahmegerät starten und Ihnen Ihre Aufgabe kurz erläutern.

<Question: What is your planned financial project?>

<Start Recording>

Vor sich sehen Sie nun eine Website. Ihre Aufgabe ist es, sich über das Angebot auf der Website zu informieren und mit der Website Ihr <geplantes Projekt> zu realisieren. Bitte sprechen Sie hierbei laut aus, was Sie gerade tun, was Sie sehen, empfinden und was Ihnen auffällt.

Urn Game - General Instructions

Willkommen beim Experiment und vielen Dank für Ihre Teilnahme!
Bitte schalten Sie ihr Smartphone aus und sprechen Sie von nun an nicht mehr mit anderen Teilnehmern des Experiments.

Dieses Experiment dient der Untersuchung von ökonomischem Entscheidungsverhalten. Sie können dabei Geld verdienen. Dieses wird Ihnen im Anschluss an das Experiment privat und in bar ausbezahlt. Während des Experiments wird ihr Entscheidungsverhalten aufgezeichnet und in der späteren Analyse ausgewertet.

Das Experiment - Überblick
Das Experiment besteht aus insgesamt <x> Teilen:

<table of contents>

Die folgenden Teile werden Ihnen nun kurz erläutert.

1. Verständnisfragen
Bevor das Experiment beginnt, werden Ihnen an Ihrem Bildschirm zunächst einige Verständnisfragen zu den Regeln dieses Experiments gestellt. Geben Sie bitte die jeweiligen Antworten in Ihren Computer ein. Sie erhalten allgemeine Fragen um sicher zu stellen, dass Sie die Anleitung gelesen und verstanden haben.

<experiment specific task description>

Fragebogen
Nach Beendigung des Urnenspiels, wird ein Fragebogen in einem Browserfenster geöffnet, bitte beantworten Sie ihn und warten Sie anschließend in Ihrer Kabine. Sie werden von dem Experimentalleiter abgeholt und erhalten Ihre Auszahlung.

Gewinnmöglichkeit: Für das Ausfüllen der Fragebögen erhalten Sie einen fixen Teilnehmerbetrag von X Euro.

Zusammenfassung Zuerst müssen Sie Verständnisfragen beantworten. Dann müssen sie ein Urnenspiel absolvieren. Das Spiel geht über mehrere Phasen, wobei jede Phase aus zwei Runden / Ziehungen besteht. Anschließend müssen Sie einen Fragebogen ausfüllen.

Wir bitten Sie, während des Experiments nicht zu sprechen und sich nicht in Ihrer Konzentration stören zu lassen.

Verständnisschwierigkeiten? Wenn Sie Fragen haben, so machen Sie die Experimentleitung im Anschluss an diese Anleitung per Handzeichen auf sich aufmerksam. Richten Sie Ihre Frage so leise wie möglich an die Experimentleitung und sprechen Sie nicht mit den anderen Teilnehmern.

Hilfsmittel An Ihrem Platz finden sie einen Kugelschreiber und Taschenrechner (Achtung: Punkt- vor Strichrechnung wird von dem Taschenrechner nicht berücksichtigt!). Diese sind bitte nach dem Experiment am Tisch liegen zu lassen.

Instructions Urn Game - Version 1a

Im folgenden Experiment gibt es zwei Urnen, die eine unterschiedliche Anzahl an Kugeln beinhalten. Sie ziehen zweimal jeweils eine Kugel mit Zurücklegen aus den Urnen (2 x ziehen). Danach werden die Urnen neu gemischt. Ihr Ziel ist es möglichst oft eine schwarze Kugel zu ziehen, da ihre Auszahlung von den gezogenen Kugeln abhängt.

<screenshot 1 of the urngame user interface>

Das Urnenspiel besteht aus 40 Phasen mit jeweils 2 Ziehungen (80 Runden). Pro Runde können Sie immer nur eine Kugel aus eine der Urnen ziehen. Hierzu stehen Ihnen die Knöpfe Linke Urne" für die linke Urne und „Rechte Urne" für die rechte Urne zur Verfügung. Jede zweite Phase steht ihnen außerdem der Knopf „Entscheidung Ablehnen" zur Verfügung. Mit diesem Knopf legen Sie sich für keine der Urnen fest sondern erhalten eine geringere aber fixe Auszahlung.

<screenshot 2 of the urngame user interface>

Aufgabe: Ihre Aufgabe besteht darin möglichst oft eine schwarze Kugel zu ziehen. Alle zwei Phasen können Sie eine Entscheidung ablehnen ("Entscheidung Ablehnen"-Knopf).

Gewinnmöglichkeit: Ihre Auszahlung im Experiment hängt davon ab, wie oft sie die schwarze Kugel ziehen. Je häufiger sie dies tun, desto mehr Geld erhalten Sie. Für jede richtige Kugel erhalten Sie x Euro. Wenn Sie den Knopf „Decline" drücken und damit eine Entscheidung für eine der Urnen ablehnen, erhalten Sie x Euro. Um die Entscheidungsablehnung zu verdeutlichen, wird dann angezeigt, dass Sie eine graue Kugel gezogen haben.

Verteilung der Kugeln: Es gibt insgesamt zwei mögliche Zustände der Welt. Je nachdem sind die Kugeln in den Urnen verteilt:

<table with distributions of balls>

Die Verteilung der Zustände „up" and „down" ist zufällig und gleich häufig (je 50 Prozent). Ebenfalls bleibt sie über eine Phase bzw. zwei Ziehungen konstant (Runde 1 und Runde 2, Runde 3 und 4 usw.). Danach werden die Kugeln neu gemischt. Das heißt Sie können nur von Runde 1 auf Runde 2 Rückschlüsse auf die Welt ziehen. Nie jedoch von Runde 2 auf die nachfolgenden Runden.

Im Anschluss an das Urnenspiel erhalten Sie einen Fragebogen, für den Sie eine fixe Vergütung erhalten.

Instructions Urn Game - Version 1b

Im folgenden Experiment gibt es zwei Urnen, die eine unterschiedliche Anzahl an Kugeln beinhalten. Sie ziehen zweimal jeweils eine Kugel mit Zurücklegen aus den Urnen (2 x ziehen pro Phase). Danach werden die Urnen neu gemischt. Ihr Ziel ist es möglichst oft eine schwarze Kugel zu ziehen, da ihre Auszahlung von den gezogenen Kugeln abhängt.

Jede zweite Phase, wird der Computer für Sie die erste von zwei Entscheidungen treffen. Die Auswahl des Computers erfolgt zufällig. Pro Runde können Sie immer nur eine Kugel aus eine der Urnen ziehen. Hierzu stehen Ihnen die Knöpfe „Linke Urne“ für die linke Urne und „Rechte Urne“ für die rechte Urne zur Verfügung. Wenn der Computer für Sie eine Urne auswählt, können Sie in der Ziehung nur die ausgewählte Urne wählen. Somit besteht das Urnenspiel aus je 2 mal 40 Phasen mit jeweils 2 Ziehungen (160 Runden oder 80 Phasen).

Verteilung der Kugeln: Es gibt insgesamt zwei mögliche Zustände der Welt. Je nachdem sind die Kugeln in den Urnen verteilt:

<table with distributions of balls>

Die Verteilung der Zustände „up“ and „down“ ist zufällig und gleich häufig (je 50 Prozent). Ebenfalls bleibt sie über eine Phase bzw. zwei Ziehungen konstant (Runde 1 und Runde 2, Runde 3 und 4 usw.). Danach werden die Kugeln neu gemischt. Das heißt Sie können nur von Runde 1 auf Runde 2 Rückschlüsse auf die Welt ziehen. Nie jedoch von Runde 2 auf die nachfolgenden Runden.

Aufgabe: Ihre Aufgabe besteht darin möglichst oft eine schwarze Kugel zu ziehen.

Gewinnmöglichkeit: Ihre Auszahlung im Experiment hängt davon ab, wie oft sie die schwarze Kugel ziehen. Je häufiger sie dies tun, desto mehr Geld erhalten Sie. Für jede schwarze Kugel erhalten Sie x Euro.

Instructions Urn Game - Version 2

Bei dem Urnenspiel Version 2 handelt es sich um eine Variante der ersten Version (Version 1, siehe oben). Es gibt erneut zwei Urnen, die eine unterschiedliche Anzahl an Kugeln beinhalten. Ihr Ziel ist es möglichst oft eine schwarze Kugel zu ziehen, da ihre Auszahlung von den gezogenen Kugeln abhängt.

Das Urnenspiel besteht wieder aus 40 Phasen mit jeweils 2 Ziehungen (80 Runden). Pro Runde können Sie immer nur eine Kugel aus eine der Urnen ziehen. Hierzu stehen Ihnen die Knöpfe „Linke Urne“ für die linke Urne und „Rechte Urne“ für die rechte Urne zur Verfügung.

Die Kugeln sind exakt gleich, wie davor verteilt.

<table with distributions of balls>

Jedoch haben jetzt die Möglichkeit beliebig oft einen Testball aus eine der Urnen zu ziehen, bevor Sie sich entscheiden müssen. Allerdings „kostet“ Sie jeder Testversuch 0,001 Euro. Das heißt, jedes Mal wenn Sie sich entscheiden einen Testball zu ziehen, wird ihnen der Zehnte Teil eines Euro-Cents von Ihrer finalen Auszahlung abgezogen. Sie können beliebig viele Testbälle ziehen bevor Sie sich entscheiden.

Aufgabe: Ihre Aufgabe besteht darin möglichst oft eine schwarze Kugel zu ziehen.

Gewinnmöglichkeit: Ihre Auszahlung im Experiment hängt davon ab, wie oft sie die schwarze Kugel ziehen. Je häufiger sie dies tun, desto mehr Geld erhalten Sie. Für jede richtige Kugel erhalten Sie x Euro, für jeden Test verlieren Sie 0,001 Euro.

Instructions Urn Game - Version 3

Bei dem Urnenspiel Version 3 handelt es sich um eine Variante der ersten beiden Versionen (Version 1 und Version 2, siehe oben). Hier zieht der Computer eine Stichprobe aus eine der beiden Urnen. Das Ergebnis wird Ihnen Zug für Zug angezeigt. Sie müssen nach jedem Zug sagen mit welcher Wahrscheinlichkeit es sich Ihrer Meinung nach um die Urne mit den mehrheitlich schwarzen Kugeln handelt (+/- 5 Prozent Toleranz).

<table with distributions of balls>

Nach 10 Bällen wird wieder eine der beiden Urnen zufällig neu ausgewählt und das Spiel beginnt von vorne. Insgesamt müssen sie 5-mal anhand einer Stichprobe von 10 Bällen die Wahrscheinlichkeit anhand der Stichprobe raten. Für jede korrekte Antwort erhalten Sie x Euro.

Aufgabe: Ihre Aufgabe besteht darin die Wahrscheinlichkeit, dass es sich um die Urne mit überwiegend schwarzen Bällen handelt zu bestimmen.

Gewinnmöglichkeit: Ihre Auszahlung im Experiment hängt davon ab, wie ob sie die korrekte Wahrscheinlichkeit anhand den Informationen angeben (+/- 5 Prozent Toleranz) für die Urne angeben. Je häufiger sie dies tun, desto mehr Geld erhalten Sie. Für jede richtige Antwort erhalten Sie x Euro.

Instructions Distraction Task

Im Merkspiel werden Ihnen jeweils ein Trigram (eine Abfolge von drei zufälligen Buchstaben), sowie eine dreistellige Zahl angezeigt. Dann blinkt eine Kugel bis zu 12 Mal auf. Jedes Mal, wenn die Kugel die Farbe wechselt, ziehen Sie 3 von der angezeigten Zahl ab. Im Anschluss werden sie gebeten, entweder das Trigram oder die Zahl (abzüglich 3 für jeden Farbwechsel der Kugel) einzugeben.

Aufgabe: Ihre Aufgabe besteht daraus sich das Trigram oder die Zahl korrekt zu merken.

Gewinnmöglichkeit: Für jede korrekte Antwort erhalten Sie x Euro.

C Samples Bayesian Updating Task

The different samples and their related posterior probabilities in the Bayesian updating task.

Table 28: Set 1 Bayesian Updating Task.

Round	Sample	Posterior Probability
1	○	0.33
2	○○	0.2
3	○ ○ ○	0.11
4	○ ○ ○●	0.2
5	○ ○ ○ ● ○	0.11
6	○ ○ ○ ● ○○	0.06
7	○ ○ ○ ● ○ ○ ○	0.03
8	○ ○ ○ ● ○ ○ ○ ○○	0.02
9	○ ○ ○ ● ○ ○ ○ ○ ○ ●	0.3
10	○ ○ ○ ● ○ ○ ○ ○ ○ ●●	0.6

Table 29: Set 2 Bayesian Updating Task.

Round	Sample	Posterior Probability
1	○	0.33
2	○●	0.5
3	○ ● ●	0.6
4	○ ● ●●	0.8
5	○ ● ● ● ●	0.88
6	○ ● ● ● ●○	0.8
7	○ ● ● ● ● ○ ●	0.88
8	○ ● ● ● ● ○ ●●	0.94
9	○ ● ● ● ● ○ ● ● ●	0.96
10	○ ● ● ● ● ○ ● ● ●●	0.98

Table 30: Set 3 Bayesian Updating Task.

Round	Sample	Posterior Probability
1	●	0.33
2	●●	0.8
3	● ● ●	0.88
4	● ● ●●	0.94
5	● ● ● ● ●	0.96
6	● ● ● ● ●○	0.94
7	● ● ● ● ● ○ ○	0.88
8	● ● ● ● ● ○ ○○	0.8
9	● ● ● ● ● ○ ○ ○ ○	0.66
10	● ● ● ● ● ○ ○ ○ ○○	0.5

Table 31: Set 4 Bayesian Updating Task.

Round	Sample	Posterior Probability
1	●	0.66
2	●○	0.5
3	● ○ ●	0.66
4	● ○ ●●	0.8
5	● ○ ● ● ○	0.66
6	● ○ ● ● ○○	0.5
7	● ○ ● ● ○ ○ ○	0.33
8	● ○ ● ● ○ ○ ○○	0.2
9	● ○ ● ● ○ ○ ○ ○ ○	0.111
10	● ○ ● ● ○ ○ ○ ○ ○○	0.6

Table 32: Set 5 Bayesian Updating Task.

Round	Sample	Posterior Probability
1	●	0.66
2	●○	0.5
3	● ○ ●	0.66
4	● ○ ●●	0.8
5	● ○ ● ● ○	0.66
6	● ○ ● ● ○●	0.8
7	● ○ ● ● ○ ● ○	0.66
8	● ○ ● ● ○ ● ○●	0.8
9	● ○ ● ● ○ ● ○ ● ○	0.66
10	● ○ ● ● ○ ● ○ ● ○●	0.8

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