Nudged to win:
Designing robo-advisory to overcome decision inertia

Research in Progress

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Abstract

Decision inertia is a serious problem in financial decision-making and thus a challenge for decision support systems. We discuss recent findings and review antecedents and consequences of decision inertia from a psychological perspective. We use these insights to develop IT-based methods designed to overcome decision inertia using psychologically optimized financial decision support systems. Furthermore, we propose an experimental study to evaluate the design features of such a system. Our work is a first step in designing adaptive decision support systems that detect situations in which the user is prone to decision inertia and react by adapting interface elements appropriately that might otherwise exacerbate decision inertia – for a specific user in a specific decision situation.

Keywords: Decision Inertia, Robo-Advisor, Financial Decision Support, Nudging, Choice Architecture.

1 Introduction

Due to the steadily increasing integration of information systems in everyday life and the ubiquity of digital technologies, the digitalisation of offline everyday activities has not stopped at financial decision-making (Alt and Puschmann, 2012, 2016). As a consequence, new digital financial services such as "robo-advisors" have begun to transform offline financial advice services into digital processes. Robo-advisors are digital platforms guiding customers through an automated (investment) advisory process based on interactive and intelligent user assistance components (blinded for review; Sironi, 2016). These investment support systems have many possible uses in financial decision support, and differ from existing services like online investment platforms or online brokerage on two different conceptual levels: customer assessment and customer portfolio management. While traditional investor profiling has been conducted during personal interviews and human interaction, robo-advisors replace this process by online questionnaires and self-reporting processes. In these steps, the investment purpose and risk affinity is measured and quantified by automated algorithms and risk models comprising the profiling engine of a robo-advisor. Like other financial decision support systems, robo-advisors follow classical utility theoretic assumptions such as independence of preferences, or consumers' relatively invariant preferences across different contexts (Dhar and Gorlin, 2013). These assumptions are implemented and then transformed into product recommendations and investments by recommender and profiling modules of the platform.

However, findings from psychology and decision-making research suggest that many of these assumptions likely do not hold in reality. Preferences are likely to vary over time and are often generated on the spur of the moment, rather than induced by a fixed set of preferences (Dhar and Gorlin, 2013). Recent work in decision support systems has addressed this issue, for instance by developing configuration-based recommender systems that do not rely on the assumption of stable preferences over time (Scholz, Dorner, Schryen, and Benlian, 2017), or by including time decay in matrix factorization approaches for collaborative filtering (Shi, Larson, and Hanjalic, 2014).

Despite these advances, all current approaches have not considered one very common characteristic of decision makers: people tend to repeat previous decisions regardless of their (observed) outcomes (Alós-Ferrer, Hügelschäfer, and Li, 2016). This is crucial, because in so called active robo-advisory, the robo-advisor recommends periodical rebalancing to the investor, and the investor decides about the actual execution of the system's suggestion. This step is of utmost importance for the system design of robo-advisors. Obviously, a robo-advisor is rendered useless if the subsequent decision-making by the user is detrimentally biased.

Considering financial decision-making research, there are various studies suggesting that people stick to defaults even if it is not economically advantageous for them (Madrian and Shea, 2001). In a study of entrepreneur and non-entrepreneur investment behaviour, Sandri et al. report an inertia effect manifesting in the tendency to hold on too long on a suboptimal investment, regardless of rational considerations about risks of loss (Sandri, Schade, Musshoff, and Odening, 2010). Sautua reported decision inertia in an economic lottery game (Sautua, 2017). In this game, the participants repeated their previous decision even if it was economic suboptimal in a subsequent period. Additionally, in consumer decision-making, we observe a form of persistence where consumers prefer choosing a product that they have purchased in the past (Dubé, Hitsch, and Rossi, 2010). A review of Erev and Haruvy, comparing studies of decision-making from experience, emphasizes evidence for the decision inertia bias (Erev and Haruvy, 2013). These findings are in line with those of Alos-Ferrer, who concludes that decision inertia is a phenomenon related to a resistance to change in various decision-making settings (Alós-Ferrer et al., 2016). Consequently, there is an urgent need to address the following research question:

RQ1: *How should a robo-advisor be designed to help investors overcome their decision inertia bias?*

Targeting this question, we follow a choice architecture approach toward designing the investment support system (Johnson et al., 2012; Mirsch, Lehrer, and Jung, 2017; Weinmann, Schneider, and Vom Brocke, 2016). The term "choice architecture" has been suggested by Thaler and Sunstein and refers to the systematic design of the environment in which decisions are made in order to influence the outcome of the decision-making process in the most desirable way (Leonard, 2008). Choice architects have a set of tools like default values, framing, or anchoring to design the decision environment, and hence to nudge decision-makers towards a specific decision outcome (Mirsch et al., 2017) Using these tools, we derive two design features – investment defaults and message framing - with the overarching goal of helping decision makers to overcome decision inertia in robo-advisory and financial decision support system. If implemented, users should benefit from increased investment returns and desirable overall outcomes. We plan to assess the effect of these design features on financial decision-making in a laboratory experiment. In the laboratory setting we can reliably control decision-making including exogenous influences on financial decision-making. This combination of guided information system design (choice architecture and empirical evaluation of cognitive biases in financial decision support) forms a novel insight into decision support.

2 Theoretical Background

2.1 Robo-Advisory for Financial Decision Support

Robo-advisors are a very young phenomenon in finance and information systems and, as a consequence, few researchers have addressed robo-advisory. Recent robo-advisory research is presented as a subset of financial advisory research. It draws on foundations from related research areas like the development of mobile or portable financial advisory tools (Heinrich, Kilic, Aschoff, and Schwabe, 2014; Moewes, Puschmann, and Alt, 2011), the design of financial encounters (Dolata and Schwabe, 2016), and findings regarding financial decision support from more general perspective (Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012).

The recent insights robo-advisory research has drawn from this broad area of financial decision support literature focus on two aspects of robo-advisory design (blinded for review) research targeting i) the *configuration and profiling of users* (user investment behaviour), and research investigating the ii) *design of the user interface* to improve the user experience and interaction (interface design).

Most research in the first research stream, investigates robo-advisors from a customer perspective. For instance, Dolata and Schwabe propose design recommendations for the development of interactive advisory service encounters to increase the communication and reciprocity between advisor and customer (Dolata and Schwabe, 2016). Another work investigates relationship building in advisory scenarios supported by advisory applications on tabletops (Heinrich et al., 2014). These studies illustrate that financial advisory can successfully be supported by and partially transformed with IT-artefacts. They achieve an increase of customer satisfaction and perceived advisor quality. Furthermore, Kilic et al. provide evidence for a "coercing into completeness" phenomenon in IT-supported financial advisory, resulting in the tendency of customers to discuss every little aspect of the visualization of the advisor application (Kilic, Heinrich, and Schwabe, 2015). Based on a customer study, they derive design recommendations to increase the quality of the advisory profiling and product recommendation and to avoid this phenomenon. Other work focuses on rather technical aspects like Dziarstek et al., who develop a robo-advisor architecture based on user requirements to digitalize traditional advisory and to make the configuration and profiling of customers more efficient (Dziarstek et al., 2004). Musto et al., who provide recommendations for an advisory system drawing on case-based recommender systems (Musto, Semeraro, Lops, Gemmis, and Lekkas, 2015).

The second research stream focusses on the design of robo-advisor user interfaces. In particular, this area generated considerable research interest, because robo-advisors lack a human advisor that could react responsively to ad-hoc customer problems (blinded for review). Furthermore, findings from IT-supported financial advisory suggest that digital advisory does not improve financial concepts, and that trust in these IT-based recommendations is quite low (Heyman and Artman, 2015). However, other studies report that a carefully designed IT-based advisory application increases the value of the advisory service for the users (Nueesch, Puschmann, and Alt, 2014).

Blinded for review provide insights from design science research targeting the development and design of a robo-advisor (blinded for review). Based on insights from three design cycles of the development of a robo-advisor for the German market, a requirements model is derived and evaluated. Other work evaluates specific design recommendations, like targeting the transparency in advisory service encounters based on a design science research cycle and provides design decisions to overcome the lack of transparency by providing cost information features along the advisory process (Nussbaumer, Matter, à Porta, and Schwabe, 2012; Nussbaumer, Matter, and Schwabe, 2012).

Ruf et al. derived design principles for tablet-based financial advisory that also provide insights for the user interface design of robo-advisors (Ruf, Back, and Weidenfeld, 2015). In a follow-up study, these requirements were evaluated with a multi-method approach based on the requirement data model (Ruf, Back, Bergmann, and Schlegel, 2015). On a more general level, Anderson and colleagues investigated the influence of web service strategy on successful implementation of financial web services (Lawler et al., 2005), as for instance robo-advisors.

Overall, existing robo-advisor literature has explored design requirements and user-interface components targeting the understanding of the customer and decreasing negative side effects like the "coercing into completeness" phenomenon. However, the reduction of biases like decision inertia, which have serious implications for financial decision-making and decision support, has yet to be addressed.

2.2 Decision Inertia in Financial Decision-making

In financial decision support literature, there are an ever-increasing number of studies documenting that financial decision-makers deviate systematically from normative finance (Bhattacharya et al., 2012). For instance, studies report that decision-makers exhibit a suboptimal home bias, i.e. the tendency to prefer investments in geographically local companies (Calvet, Campbell, and Sodini, 2007; Zhu, 2002) and that decision-makers trade too often instead of keeping their investments (Odean, 1998).

A rather recently discovered bias that generated considerable research interest is decision inertia. The concept of decision inertia has been used in decision-making research to describe a phenomenon related to an individual's resistance to change (Alós-Ferrer et al., 2016). In particular, decision inertia describes the decision-maker's tendency to repeat the previous decision regardless of the (observable) consequences, even if it is outright inferior to other options (Sautua, 2017; blinded for review; Alós-Ferrer et al., 2016; Dutt and Gonzalez, 2012). Empirical findings from financial decision support literature report that decision inertia reflects an important aspect of financial investment decision-making (Agnew, Balduzzi, and Sunden, 2003; Madrian and Shea, 2001). A review of Erev and Haruvy illustrates the influence of decision inertia in numerous economic experiments and studies (Erev and Haruvy, 2013).

However, although decision inertia has been reported in different scenarios, solid knowledge about the cognitive foundations and cognitive drivers of this irrational phenomenon is rather limited (Alós-Ferrer et al., 2016). Recent studies report an influence of consistency-seeking and the motivational factor "preference for consistency" on decision inertia (Alós-Ferrer et al., 2016), while other studies of repeated decision-making reject this relationship (Zhang, Cornwell, and Higgins, 2014). Other economic studies provide support that decision inertia could be driven by indecisiveness, the preference for decision avoidance (Sautua, 2017), or affective responses and regret (Charness and Levin, 2005; Sautua, 2017).

A study investigating entrepreneurial investment decision-making reported the decision inertia effect and showed that it occurred independent of professional background or experience of the participants (real entrepreneurs vs. students and non-students) (Sandri et al., 2010). Decision inertia was not moderated by common factors like gender, age, or risk propensity. The authors concluded that a decision inertia training (teaching statistical reasoning) could decrease the decision inertia effect. Because this could be integrated in robo-advisor systems, we argue that a robo-advisor should help investors to overcome this bias. In line with the previous argument, we stress the need to target the decision inertia effect from the system design perspective.

In summary, first attempts to understand the cognitive foundations of decision inertia exist and factors influencing this phenomenon have been identified. At this point, we strive for an interdisciplinary research approach that combines information systems research with profound insights from the decision-making literature to design training modules to be integrated in robo-advisory processes and to design the choice environment to reduce decision inertia. This can be realized by adapting the choice environment of the robo-advisor based on insights from choice architecture.

2.3 Overcoming Decision Inertia with Choice Architecture and Nudging

In choice architecture, nudges are simple behavioural interventions or design decisions that push individuals towards the option they would have chosen if they would not be affected by bounded rationality (Thaler, Sunstein, and Balz, 2014; Thaler Richard and Sunstein Cass, 2008). For that purpose, choice architects make use of findings from behavioural economics and the psychology of decision-making to encourage or discourage decision-makers inclination to rely on psychological shortcuts. Many instruments have been designed to approach this goal, like the strategical design of choice menus, defaults, information wording and many other (Johnson et al., 2012). So far, nudges have become an established toolkit for choice architects like policymaker (Sugden, 2009), user-interface designer (Koch 2017; Jameson et al., 2014), or financial advisory (Thaler and Benartzi, 2004) to alter the decision-making of participants in a positive way. In particular, with respect to decision inertia, first attempts have been successfully implemented in environmental policy. By setting the pro-environmental options as a default, the paper pollution of the Rutgers University could be reduced about 7 million pages (Croson and Treich, 2014).

In information systems research so called “digital nudges” (Mirsch et al., 2017) – a specific subset of nudges – gained increasing popularity. Digital nudging uses user interface design elements to point the decisions of users towards the desired choice. For that purpose, choice architects in information systems could for instance rely on design elements like information wording, notifications, or specific assistance features. However, while traditional nudges are an established method to overcome behavioural biases, the concept of digital nudging is very young and only few researchers in information systems have made use of digital nudges (Hummel, Schacht, and Maedche, 2017). Nevertheless, there exist studies that use digital nudges or behavioural interventions in information systems research to reduce biases in user-generated online reviews (Schneider, Weinmann, and Vom Brocke, 2015), to support environmentally friendly decision-making in online booking (Székely, Weinmann, and Vom Brocke, 2016), or to design adaptive nudges for multi-channel choices in banking (Hummel et al., 2017). Stryja et al. have focused on a choice architecture approach to overcome resistance in technology adoption (Stryja, Dorner, and Riefle, 2017; Stryja, Satzger, and Dorner, 2017), which is a phenomenon linked to decision inertia. In their work, they propose defaults and priming as possible nudges to overcome the resistance to change in innovation acceptance, however they found a significant influence of default nudging only (Stryja, Dorner et al., 2017).

In sum, a strategically designed choice architecture has the potential to help decision-makers to reach an optimal outcome in financial decision-making. In our case, this would be to reduce decision inertia in financial decision-making. For that purpose, we propose the following nudges to overcome decision inertia in financial decision-making.

3 Research Model

Our dependent variable is decision inertia, or the tendency to repeat the previous decision regardless of the consequences, even if it is clearly inferior to other options (Alós-Ferrer et al., 2016; Sautua, 2017). In the context of an active robo-advisory, decision inertia would manifest as the tendency to repeat the last investment, regardless of the outcome and the suggestion of the robo-advisor to select another one.

Choice architecture provides the theoretical foundation for our behavioural intervention to overcome this decision inertia phenomenon in financial advisory. Which nudges should be applied depends on the design strategy of the robo-advisor (Silver, 1991). In our case, we want to select nudges that are as minimal invasive as possible. Furthermore, the nudges should be low-cost and easy to implement. Taking these considerations into account, we selected the following nudges.

Firstly, we propose default nudging as a first design feature to overcome decision inertia. From choice architecture research we know that decision-makers have a status quo bias, manifested as the tendency to avoid leaving the status quo (Sunstein, 2017). We assume that we can set a new status quo in the choice environment by preselecting the optimal option for the decision-maker. As a consequence, the decision-maker will perceive the new option as status quo, and will be less likely to rely on decision inertia. Based on our design strategy, we assume that investors use robo-advisors because they want to relinquish part of their responsibility (e.g. make orders on the market by their own or gather information about investments). On the other hand, they want to have the possibility to monitor their investment, which is not possible on active fonds and comparable financial investment products. And they want to retain control or the feeling of control of 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 his feeling of control.

H1: *Preselecting the optimal option as default option, will decrease decision inertia in situations where inertia is suboptimal.*

Another popular nudge is wording or framing. Such nudges provide information in one of two semantically virtually equivalent ways (framing). For example, the messages "*Investment A is a loss*" and "*Investment A is no win*" convey the same information. However, from cognitive psychology and message framing research, we know that people differ in the way they process these two messages due to different reference points (Kühberger, 1998). In particular, regulatory fit theory provides a theoretical foundation how framed message are processed by decision-makers (Cesario, Corker, and Jelinek, 2013). According to this theory, people differ in an individual promotion and prevention focus. Promotion-focused individuals make decisions regardless of the consequences, because they pursue situations that represent a gain to them and are relatively indifferent to situations that represent a loss to them. Prevention-focused individuals decide the other way round. If such decision-makers have to make a decision in an environment that fits to their inherent regulatory focus, the situation is called a regulatory fit (Cesario et al., 2013; Higgins, 2000). Regulatory fit enhances cognitive and motivational processes and the decision-makers are more dedicated towards goal achievement (Keller and Bless, 2006; Shah, Higgins, and Friedman, 1998).

By facing investors with a choice environment that is framed in accordance with their regulatory focus, we hope to increase ease of information processing and consequently decrease the tendency to rely on suboptimal biases and heuristics. In practice this could be integrated easily in existing robo-advisors. In the profiling step, they face users with many questions to configure the risk-profiling and some more questions to measure the inherent regulatory focus of the participants could be done easily. As a consequence, this regulatory fit (or what we call adaptive wording) will decrease the decision inertia effect.

H2: *Adaptive wording is negatively associated with the tendency to rely on decision inertia*

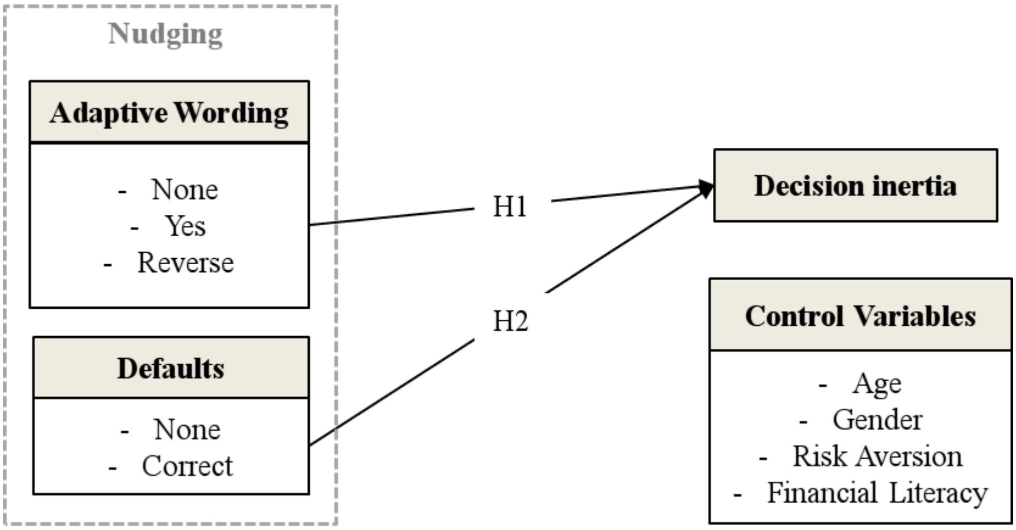

Figure 1. *Research model with the two nudges "defaults" (H1) and "adaptive wording" (H2) to reduce decision inertia, and the control variables.*

4 Proposed Study

4.1 Experimental task

In our study, decision inertia is defined as the 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). Following established decision inertia research, we rely on a dual-choice belief-updating task (so called dual-choice paradigm) to measure decision inertia (blinded for review; Alós-Ferrer et al., 2016; Charness and Levin, 2005). In this task, participants are faced with two subsequent decisions. In each decision the participants can choose between two (or more) options. The options have different outcome distributions, and successful outcomes are rewarded. However, which distribution belongs to which option is unknown to the participants. As a consequence, they make the first decision without any information. After the first decision, they receive feedback about the outcome of their choice and can make qualified guesses about the probability that the previous option was the choice with the better or worse distribution. Furthermore, they can compute the probability of the optimal decision in the next trial based on Bayes' Theorem.

In our case, we plan to prepare a scenario and asking the participants to invest a specific amount of money with our robo-advisor implemented in the Brownie framework for experiments in IS research (blinded for review). The robo-advisor will contain all the relevant phases (Configuration, Matching and Maintenance) and confront the participants with at least two investment options. We investigate if the provided nudges influence the tendency to behave suboptimal in this task and if the participants fall victim to the decision inertia bias.

4.2 Measures

We operationalize decision inertia as the proportion of participants that repeat a decision, even if it was experienced as disadvantageous (e.g. if switching the investment would be optimal in sense of Bayes' Theorem). Furthermore, we use self-reports to assess risk-aversion (Dohmen et al., 2011), and gender and age as control variables. Furthermore, we plan to make a pre-test to evaluate the validity of our constructs and to make sure that our task can reproduce decision inertia in the lab.

4.3 Participants

We plan to conduct the experiment in the behavioural research lab of a German university. The lab consists of 40 identical cabins and allows measuring the behaviour of our participants objectively. Furthermore, we plan to use eye-tracking to investigate if the participants noticed our nudges, and if there are differences in the perception, which has been done in other studies to test the validity of the nudges (Hummel et al., 2017). 50 students from our pool will be invited to participate in our study.

4.4 Procedure

Prior to the study, participants receive a fixed payment and are asked to invest the money in our provided robo-advisory solution. Furthermore, the participants are informed about the procedure and the two possible probability distributions of the investment game. To address our three hypotheses, we propose to carry out the following steps.

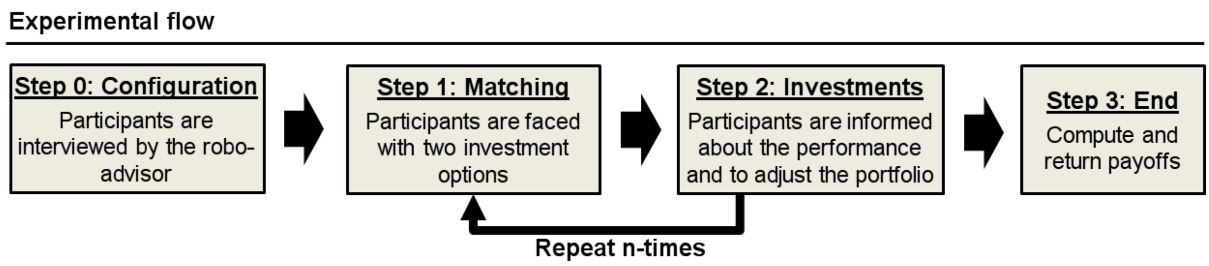

Figure 2. Proposed experimental procedure to investigate decision inertia in robo-advisory

5 Conclusion and Outlook

In our study, we aim at contributing to a deeper understanding of the mechanisms underlying decision inertia. In particular, we focus on a specific facet of inertia: the tendency to repeat a previous choice, regardless of the consequences (Alós-Ferrer et al., 2016). We propose that decision inertia can be reduced by choice architecture.

From an IS perspective, it is of paramount importance to better understand the antecedents of decision inertia if we are to develop interfaces and algorithms that can help decision-makers avoid falling into the trap of repeating unfavourable prior decisions. With the insights that we plan to generate with this proposed study, we aim to analyse existing decision support systems in various contexts and developing adaptations that can better address this issue. Our research applies to both consumer (and this is where our focus lies for the moment) and business decision-making, e.g. in forecasting support systems.

The proposed initial experimental study is intended to form the basis for future research at the intersection of psychology and decision support systems. Based on the insights drawn from the planned experiment, we intend to further examine antecedents and consequences of decision inertia from a psychological perspective and to use these insights to develop IT-based counter-measures. One possible avenue is designing adaptive decision support systems that detect situations in which the user is prone to decision inertia and react by changing those interface elements that likely exacerbate decision inertia – for a specific user in a specific decision situation. Potential applications include decision support in a business context, such as forecast support systems, and for consumers in e-commerce, and disaster management besides financial decision support.

Thus, our research not only provides a theoretical basis for understanding inertia phenomena in financial decision support in general, and in robo-advisory support in particular, but also suggests interventions to overcome it. Considering that an increasing number of decisions are made in digital environments or supported by digital technology, we believe that optimally designed robo-advisory system will certainly help decision makers to disable decision inertia.

References

Agnew, J. and Balduzzi, P. and Sunden, A. (2003). “Portfolio choice and trading in a large 401 (k) plan”. *The American economic review*, *93*(1), 193–215.

Alós-Ferrer, C. and Hügelschäfer, S. and Li, J. (2016). “Inertia and decision making”. *Frontiers in psychology*, *7*.

Alt, R. and Puschmann, T. (2012). “The rise of customer-oriented banking-electronic markets are paving the way for change in the financial industry”. *Electronic Markets*, *22*(4), 203–215.

Alt, R. and Puschmann, T. (2016). *Digitalisierung der Finanzindustrie*: Springer.

Bhattacharya, U. and Hackethal, A. and Kaesler, S. and Loos, B., and Meyer, S. (2012). “Is unbiased financial advice to retail investors sufficient? Answers from a large field study”. *The Review of Financial Studies*, *25*(4), 975–1032.

Calvet, L. E. and Campbell, J. Y. and Sodini, P. (2007). “Down or out: Assessing the welfare costs of household investment mistakes”. *Journal of Political Economy*, *115*(5), 707–747.

Cesario, J. and Corker, K. S. and Jelinek, S. (2013). “A self-regulatory framework for message framing”. *Journal of Experimental Social Psychology*, *49*(2), 238–249.

Charness, G. and Levin, D. (2005). “When optimal choices feel wrong: A laboratory study of Bayesian updating, complexity, and affect”. *The American economic review*, *95*(4), 1300–1309.

Croson, R. and Treich, N. (2014). “Behavioral environmental economics: promises and challenges”. *Environmental and Resource Economics*, *58*(3), 335–351.

Dhar, R. and Gorlin, M. (2013). “A dual-system framework to understand preference construction processes in choice”. *Journal of Consumer Psychology*, *23*(4), 528–542.

Dohmen, T. and Falk, A. and Huffman, D. and Sunde, U. and Schupp, J. and Wagner, G. G. (2011). “Individual risk attitudes: Measurement, determinants, and behavioral consequences”. *Journal of the European Economic Association*, *9*(3), 522–550.

Dolata, M. and Schwabe, G. (2016). “More interactivity with IT support in advisory service encounters?” *Mensch und Computer 2016-Tagungsband*.

Dubé, J. and Hitsch, G. J. and Rossi, P. E. (2010). „State dependence and alternative explanations for consumer inertia”. *The RAND Journal of Economics*, *41*(3), 417–445.

Dutt, V. and Gonzalez, C. (2012). “The role of inertia in modeling decisions from experience with instance-based learning”. *Frontiers in psychology*, *3*.

Dziarstek, C. and Farnschläder, F. and Gilleßen, S. and Süßmilch-Walther, I. and Winkler, V. and Merbach, P. and Sandkuhl, K. (2004). “A user-aware financial advisory system”. In: *Proceedings Multikonferenz Wirtschaftsinformatik (MKWI)*, *2*, 217–229.

Erev, I. and Haruvy, E. (2013). “Learning and the economics of small decisions”. *The handbook of experimental economics*, *2*.

Heinrich, P. and Kilic, M. and Aschoff, F.-R. and Schwabe, G. (2014). *Enabling relationship building in tabletop-supported advisory settings*: ACM.

Heyman, S. and Artman, H. (2015). *Computer support for financial advisors and their clients: Co-creating an investment plan*: ACM.

Higgins, E. T. (2000). “Making a good decision: value from fit”. *American psychologist*, *55*(11), 1217.

Hummel, D. and Schacht, S. and Maedche, A. (2017). “Designing Adaptive Nudges for Multi-Channel Choices of Digital Services: A Laboratory Experiment Design”. In: *Proceedings of the Twenty-Fith Conference on Information Systems (ECIS).*

Jameson, A. and Berendt, B. and Gabrielli, S. and Cena, F. and Gena, C. and Vernero, F. and Reinecke, K. (2014). “Choice architecture for human-computer interaction”. *Foundations and Trends in Human–Computer Interaction*, *7*(1–2), 1–235.

Johnson, E. J. and Shu, S. B. and Dellaert, B. G. C. and Fox, C. and Goldstein, D. G. and Häubl, G. and Schkade, D. (2012). “Beyond nudges: Tools of a choice architecture“. *Marketing Letters, 23*(2), 487–504.

Keller, J. and Bless, H. (2006). “Regulatory fit and cognitive performance: the interactive effect of chronic and situationally induced self-regulatory mechanisms on test performance“. *European Journal of Social Psychology*, *36*(3), 393–405.

Kilic, M. Heinrich, P. and Schwabe, G. (2015). “Coercing into Completeness in Financial Advisory Service Encounters“. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1324–1335.

Koch, O. F. (2017). “Nudges as Conversion Funnel Enhancers in Digital Business Models”. PhD thesis. Technische Universität Darmstadt.

Kühberger, A. (1998). “The influence of framing on risky decisions: A meta-analysis“. *Organizational behavior and human decision processes, 75*(1), 23–55.

Lawler, J. and Anderson, D. and Howell-Barber, H. and Hill, J. and Javed, N. and Li, Z. (2005). “A study of web services strategy in the financial services industry“. *Information Systems Education Journal*, *3* (3), 1–25.

Leonard, T. C. (2008). Richard H. Thaler, Cass R. Sunstein, “Nudge: Improving decisions about health, wealth, and happiness“. *Constitutional Political Economy*, *19* (4), 356–360.

Madrian, B. C. and Shea, D. F. (2001). “The power of suggestion: Inertia in 401 (k) participation and savings behavior“. *The Quarterly Journal of Economics, 116* (4), 1149–1187.

Mirsch, T. Lehrer, C. and Jung, R. (2017). “Digital Nudging: Altering User Behavior in Digital Environments“. In: *Proceedings der 13. Internationalen Tagung Wirtschaftsinformatik (WI 2017).*

Moewes, T. and Puschmann, T. and Alt, R. (2011). “Service-based Integration of IT-Innovations in Customer-Bank-Interaction“.

Musto, C. and Semeraro, G. and Lops, P. and Gemmis, M. de and Lekkas, G. (2015). “Personalized finance advisory through case-based recommender systems and diversification strategies“. *Decision Support Systems, 77*, 100–111.

Nueesch, R. and Puschmann, T. and Alt, R. (2014). “Realizing value from tablet-supported customer advisory: cases from the banking industry“. In: *Proceedings of 27th Bled eConference Slovenia*, 292–305.

Nussbaumer, M. P. and Matter, D. I. I. and à Porta, G. R. and Schwabe, G. (2012). Designing for Cost Transparency in Investment Advisory Service Encounters. *Business and Information Systems Engineering*, *4*(6), 347–361.

Nussbaumer, P. and Matter, I. and Schwabe, G. (2012). ““Enforced” vs.“Casual” Transparency-Findings from IT-Supported Financial Advisory Encounters“. *ACM Transactions on Management Information Systems (TMIS), 3*(2), 11.

Odean, T. (1998). “Are investors reluctant to realize their losses? “ *The Journal of finance*, *53*(5), 1775–1798.

Ruf, C. and Back, A. and Bergmann, R. and Schlegel, M. (2015). *Elicitation of Requirements for the Design of Mobile Financial Advisory Services--Instantiation and Validation of the Requirement Data Model with a Multi-method Approach*: IEEE.

Ruf, C. and Back, A. and Weidenfeld, H. A. (2015). *Designing Tablet Banking Apps for High-Net-Worth Individuals: Specifying Customer Requirements with Prototyping.*

Sandri, S. and Schade, C. and Musshoff, O. and Odening, M. (2010). “Holding on for too long? An experimental study on inertia in entrepreneurs’ and non-entrepreneurs’ disinvestment choices“. *Journal of Economic Behavior and Organization, 76* (1), 30–44.

Sautua, S. I. (2017). “Does uncertainty cause inertia in decision making? An experimental study of the role of regret aversion and indecisiveness“. *Journal of Economic Behavior and Organization*, *136*, 1–14.

Schneider, C. and Weinmann, M. and Vom Brocke, J. (2015). “Choice architecture: Using fixation patterns to analyze the effects of form design on cognitive biases“. In *Information Systems and Neuroscience*, 91–97.

Scholz, M. and Dorner, V. and Schryen, G. and and Benlian, A. (2017). “A configuration-based recommender system for supporting e-commerce decisions“. *European Journal of Operational Research*, *259*(1), 205–215.

Shah, J. and Higgins, T. and Friedman, R. S. (1998). “Performance incentives and means: how regulatory focus influences goal attainment“. *Journal of personality and social psychology*, *74* (2), 285.

Shi, Y. and Larson, M. and Hanjalic, A. (2014). “Collaborative filtering beyond the user-item matrix: A survey of the state of the art and future challenges“. *ACM Computing Surveys (CSUR)*, *47* (1), 3.

Silver, M. S. (1991). “Decisional guidance for computer-based decision support“. *MIS quarterly*, 105–122.

Sironi, P. (2016). *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification*: John Wiley and Sons.

Stryja, C. and Dorner, V. and Riefle, L. (2017). *Overcoming Innovation Resistance beyond Status Quo Bias-A Decision Support System Approach (Research-in-Progress).* In: *Proceedings of the 50th Hawaii International Conference on System Sciences*

Stryja, C. and Satzger, G. and Dorner, V. (2017). “A Decision Support System Design to Overcome Resistance Towards Sustainable Innovations”. In: *Proceedings of the 25th European Conference on Information Systems (ECIS)*.

Sugden, R. (2009) *On nudging: A review of nudge: Improving decisions about health, wealth and happiness by Richard H. Thaler and Cass R. Sunstein.*

Sunstein, C. R. (2017). “Default Rules Are Better Than Active Choosing (Often)”. *Trends in Cognitive Sciences*.

Székely, N., Weinmann, M., and Vom Brocke, J. (2016). *Nudging People to Pay CO2 offsets-the effect of Anchors in Flight Booking Processes.*

Thaler, R. H., and Benartzi, S. (2004). “Save more tomorrow™: Using behavioral economics to increase employee saving”. *Journal of Political Economy*, *112*(S1), S164-S187.

Thaler, R. H. and Sunstein, C. R. and Balz, J. P. (2014). Choice architecture.

Thaler Richard, H. and Sunstein Cass, R. (2008). *Nudge: Improving decisions about health, wealth, and happiness.*

Weinmann, M. and Schneider, C. and Vom Brocke, J. (2016). “Digital Nudging”. *Business and Information Systems Engineering*, *58*(6), 433–436.

Zhang, S. and Cornwell, J. F. M. and Higgins, E. T. (2014). “Repeating the past: Prevention focus motivates repetition, even for unethical decisions”. *Psychological science*, *25*(1), 179–187.

Zhu, N. (2002). The local bias of individual investors.