Social Cues as Digital Nudges in Information Systems Usage Contexts

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Abstract

Analysing human cognition and decision-making has become highly relevant in information systems (IS) research. Yet, although the notion of cognitive biases has been studied for more than 40 years in psychology and other related fields, IS researchers have only recently expressed explicit interest in this phenomenon. Even more nascent is the IS stream that emphasizes the usage and understanding of biases in the favor of humanistic outcomes (e.g., the well-being of individuals) beyond previous scientific endeavors to pursue instrumental goals (e.g., the profit of companies). This fact is reflected in the recent emergence and call for digital nudges - influences that rely on heuristics and biases to guide individuals to beneficial decisions through modest adjustments of the digital choice environments. To advance the emergent research in this field, this thesis targets one of the major bias categories: the social bias (i.e., systematic errors that result from an individual's interpretation of social cues).

Within four articles, the thesis addresses the role of social cues as digital nudges in various IS usage contexts. The first two articles investigate how directly-traceable social cues can overcome service adoption hurdles: Precisely, the first article investigates how employing a verbal (i.e., platform self-disclosure) and a nonverbal social cue (i.e., message interactivity) in a conversational agent (i.e., chatbot) influence users to voluntary self-disclose private information (i.e., e-mail addresses). Moreover, the results revealed that the analysed social cues do not have individual effects, but in fact boost each other through their interaction.

The second article deals with the application of various directly-traceable social cues (e.g., pictures of human avatars) as well as the role of personalized recommendations in financial advisory services to improve investors' financial well-being. The results demonstrate that not only directly-traceable social cues but also recommendations can increase a user's perceived social presence during the interaction, which in turn influences potential investors to invest higher amounts.

The third article continues with recommendations as social cues, yet analyses them from an indirectly-traceable perspective and is devoted to investigating whether the source of the recommendation (i.e., seller or other customers) influences the acceptance of the recommendation in augmented reality applications to help customers in finding the best product for their needs. The findings indicate that customer recommendations reduce a customer's perceived fit uncertainty of a product, resulting in a higher intention to purchase of a product that previous customers recommended. However, customers refrain from adhering to an automatically-generated recommendation despite recent technological advances that may provide more personalized and thus more suitable recommendations than generic customer recommendations.

The fourth and last article examines the impact of displaying sold-out products on campaign success in reward-based crowdfunding. The valuable information indicate how potential backers make use of displayed sold-out product as social cues to derive information for their decision-making from previous backing behavior. In addition, the findings also showed that sold-out products do not have an impact on their own, however, their effect is also influenced by other factors in the environment, namely discount amount and the number of backers (i.e., another social cue). Thus, the article provides learnings for project creators on the design of reward option menus.

Overall, this thesis showcases the variety and importance of social cues in numerous applications and is, therefore, to be understood as a first approach to expanding the understudied research field. Furthermore, the results enrich previous research and elucidate various underlying explanatory mechanisms of how and why biased decision-making takes place and how these mechanisms may be used to nudge users in directions beneficial for them and for the employer of these nudges. The overarching contributions of this thesis for research consists of (1) investigating the existence and effects of various social cues on user decision-making, and (2) probing social cues in several IS usage contexts with their unique circumstances and influences, not only in a vacuum but also in conjunction with other interacting variables. Additionally, this thesis provides interesting and sometimes even counterintuitive recommendations as well as actionable and generalizable guidelines on social cues that practitioners can easily apply to various contexts.

Zusammenfassung

Das Analysieren menschlichen Denkens und Entscheidens hat in der Forschung zu Informationssystemen (IS) zunehmend an Relevanz gewonnen. Während jedoch die Idee von kognitiven Verzerrungen (d.h. cognitive biases) seit über 40 Jahren in Psychologie und anlehnenden Forschungsfeldern studiert wurde, haben IS Forscher erst vor kurzer Zeit Interesse an dem Phänomen explizit ausgedrückt. Noch jünger ist dabei die IS Strömung, die sich auf die Nutzung und das Verstehen von kognitiven Verzerrungen zugunsten von humanistischen Zielen (z.B. das Wohlbefinden von Individuen) ausrichtet, während die bisherige Forschung vor allem das Erreichen von instrumentalen Zielen (z.B. die Profite von Unternehmen) verfolgte. Diese Beschränkung der bisherigen Forschung wird hervorgehoben vor allem durch das kürzliche Erscheinen von und dem Ruf nach „digitalen Schubsern“ (d.h. digital nudges) – Beeinflussungen, die sich kognitive Verzerrungen zunutze machen, um Individuen durch mäßige Anpassungen der digitalen Umgebung zu vorteilhaften Entscheidungen zu führen. Um dieses noch junge Forschungsfeld voranzubringen, zielt die Dissertation darauf ab, Erkenntnisse zu einer wichtigen Kategorie der Verzerrungen - sozial-bedingte Verzerrungen (d.h. social biases) - zu liefern, welche als systematische Fehler in der Interpretation von sozialen Hinweisen verstanden werden können.

Innerhalb von vier veröffentlichten Artikeln addressiert die Dissertation die Rolle von sozialen Hinweisen als digitale Schubser in verschiedenen IS-Nutzungs-Kontexten. Die ersten beiden Artikel untersuchen wie direkt verfolgbare soziale Hinweise die Annahme von neuer Technologie und das Einführen eines Nutzers in einen neuen Kontext erleichtern kann. Im ersten Artikel geht es dabei um den Gebrauch eines verbalen (d.h. Selbstoffenbarung) und eines nichtverbalen sozialen Hinweises (d.h. Interaktivität der Nachricht) und wie dieser Gebrauch in einem Chatbot den Nutzer dazu beeinflusst persönliche Informationen freiwillig preiszugeben. Die Ergebnisse weisen darüber hinaus darauf hin, dass die sozialen Hinweise nicht nur individuelle Effekte besitzen, sondern dass sich die Effekte gegenseitig durch eine Interaktion verstärken.

Der zweite Artikel handelt über die Anwendung von verschiedenen direkt verfolgbaren sozialen Hinweisen und die Rolle von personalisierten Empfehlungen in digitalen Finanzverwaltern, um die Investitionsmenge von Nutzern zu erhöhen und dadurch Nutzer finanziell besser zu stellen. Die Ergebnisse demonstrieren, dass nicht nur direkt verfolgbare soziale Hinweise (z.B. ein Bild eines menschlichen Avatars) sondern auch explizite Empfehlungen die wahrgenommene

soziale Präsenz während der Interaktion erhöhen, wodurch der Nutzer die Investitionsmenge erhöht.

Der dritte Artikel fährt mit Empfehlungen als soziale Hinweise fort, analysiert jedoch ihre Wirkung aus der Perspektive wenn Nutzer die Hinweise indirekt wahrnehmen. Außerdem untersucht der Artikel ob die Quelle (d.h. Verkäufer oder andere Kunden) den Nutzer darin beeinflusst die Empfehlung zu akzeptieren und was dies für Auswirkungen hat, den Nutzer bei der Suche nach dem besten Produkt für seine oder ihre Bedarfe zu unterstützen. Die Untersuchungsergebnisse deuten darauf hin, dass Empfehlungen durch Kunden die wahrgenomme Unsicherheit eines potentiellen Kunden reduzieren, was dazu führt, dass der potentielle Kunde eine höhere Kaufbereitschaft als auch eine höhere Wahrscheinlichkeit entwickelt, das empfohlene Produkt zu kaufen. Auf der anderen Seite wirken automatisch generierte Empfehlungen des Verkäufers nicht signifikant auf die Kaufentscheidung des Nutzers, obwohl kürzlich technologische Entwicklungen andeuten, dass diese Art der Verkäuferempfehlungen durch die bessere Personalisierung auf die individuellen Bedarfe der Nutzer zu besseren Empfehlungen führen.

Der vierte und letzte Artikel untersucht die Auswirkung der Anzeige von ausverkauften Produkten auf den Erfolg von Kampagnen in Reward-Based Crowdfunding. Die Ergebnisse erklären, wie potentielle Unterstützer die angezeigten, ausverkauften Produkte als soziale Hinweise nutzen, um Informationen aus dem vergangenen Verhalten für ihre Entscheidungsfindung abzuleiten. Zusätzlich weisen die Funde darauf hin, dass ausverkaufte Produkte nicht nur einen eigenen Effekt haben, sondern auch von anderen Faktoren in der Umgebung abhängig sind, nämlich von der Höhe des Preisnachlasses und der Anzahl an bereits existierenden Unterstützern (d.h. ein anderer sozialer Hinweis). Demzufolge stellt der Artikel auch Erkenntnisse über das Menu Design von Belohnungen zur Verfügung, die Projektersteller in der Praxis nutzen können.

Zusammenfassend präsentiert die Dissertation die Vielfalt und Wichtigkeit von sozialen Hinweisen in zahlreichen Anwendungsfällen und ist daher als eine der ersten Bemühungen zu verstehen, um das bisher wenig erforschte Forschungsfeld mit Erkenntnissen zu erweitern. Darüber hinaus bereichern die Ergebnisse die bisherige Forschung und erläutern verschiedene zugrunde liegende Mechanismen darüber wie und warum verzerrte Entscheidungsfindung stattfindet und wie diese genutzt werden kann. Die größten Beiträge für die Forschung bestehen daher aus (1) der Untersuchung der Effekte von verschiedenen sozialen Hinweisen im Entscheidungsfindungsprozess und (2) dem Erforschen sozialer Hinweise in einigen IS-

Nutzungs-Kontexten mit ihren einzigartigen Umständen und Einflüssen, die mit anderen Variablen in der Umgebung interagieren. Darüber hinaus bietet die Dissertation interessante und teilweise überraschende Handlungsempfehlungen sowie leicht umsetzbare und generalisierbare Richtlinien zu sozialen Hinweisen, die Praktiker in verschiedenen Kontexten anwenden können.

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List of Abbreviations

AMT	Amazon Mechanical Turk
ANOVA	Analysis of Variance
AR	Augmented Reality
AVE	Average Variance Extracted
CA	Conversational Agent
CFA	Confirmatory Factor Analysis
CR	Customer Recommendation
H	Hypothesis
HCI	Human-Computer Interaction
HTMT	Heterotrait-Monotrait Ratio of Correlations
IS	Information Systems
IT	Information Technology
LLCI	Lower Limit of Confidence Interval
MI	Message Interactivity
ORS	Online Recommender Systems
PSD	Platform Self-Disclosure
RQ	Research Question
SD	Standard Deviation
SE	Standard Error
SR	Seller Recommendation
ULCI	Upper Limit of Confidence Interval
VIF	Variance Inflation Factor

Chapter 1: Introduction

1.1 Motivation and Research Question

Analysing human cognition and decision-making has evolved into a prime area of interest in the field of information systems (IS) research (Goes, 2013; Fleischmann et al., 2014). To comprehend human decision-making in IS, studies often rely on theories that originally stem from psychology (e.g., Davis, 1989) and other related fields. One phenomenon from psychological research - the cognitive bias - has particularly gained scholarly attention. Cognitive biases are considered systematic errors (Wilkinson and Klaes, 2017) that result from the application of "methods for arriving at satisfactory solutions with modest amounts of computation" (Simon, 1990, p.11). As a result of applying these rules of thumb (i.e., heuristics), individuals may make objectively nonrational decisions that can conclude in suboptimal outcomes for a decision-maker and other parties that are affected by the decision (Wilkinson and Klaes, 2017).

IS practice and research deal with newly-arising phenomena and contexts, such as crowdsourcing, electronic marketplaces, and recommendation systems, which are characterized by information richness and are closely connected to user decision-making. Therefore, these environments are prone to the emergence of cognitive biases (Goes, 2013). Initial IS research has started to realize and unearth the enormous potential of analysing the phenomenon of cognitive biases (e.g., Arnott, 2006; Kim and Kankanhalli, 2009). Still, although the concept of cognitive biases has been a subject in science for over 40 years (Tversky and Kahneman, 1974), research on cognitive biases in IS has been rather neglected and sporadic (e.g., Mann et al., 2008). In a scientometric analysis of top-rated publications in IS research, Fleischmann et al. (2014) found only 84 articles explicitly concerned with cognitive biases in the IS discipline over the past 20 years.

One especially interesting bias category is the social bias. Social biases arise from attitudes that are shaped by a decision-maker's relationship to other social actors. Individuals are prone to be influenced by social norms and the behaviors of others, searching for social proof and indications of how to behave appropriately in certain situations. This observation is in accordance with substantial psychological evidence that individuals are inclined to use various mental shortcuts to reduce extensive information processing effort (e.g., Chaiken, 1980; Eagly and Chaiken, 1993). A frequent result of social biases is herd behavior, in which individuals in a group act collectively without centralized direction (e.g., Scharfstein and Stein, 1990). For example, individuals may strive to possess a certain commodity that other people already own because the individuals believe that the others' choices reveal superior opportunities. Even though the individuals may not need the desired commodity, they may take steps to obtain it because they do not wish to miss out on the superior opportunities afforded to the others (i.e., bandwagon effect) (e.g., Van Herpen et al., 2009).

Against this backdrop, several contemporary researchers have called for more research on (social) influences and biases (e.g., Goes, 2013; Fleischmann et al., 2014) as well as the actionable application of digital nudges to leverage or mitigate the effects of biases (e.g., Weinmann et al., 2016; Mirsch et al., 2017). Digital nudging hereby refers to the practice of using user-interface design elements to improve the outcomes of user decision-making in digital choice environments (Weinmann et al., 2016) and has shown promising results in steering user behavior (e.g., Tietz et al., 2016; Jung et al., 2018). Yet, the number of studies on social biases and nudges in contrast to their potential and promising applications is rather low, reflecting a relatively untouched and understudied research field. Thus, this dissertation intends to extend prior research on digital nudging, specifically addressing and investigating the types of nudges that can trigger social biases through social cues to influence user behavior.

Drawing on human communication and cue utilization theory, in the thesis I consider a cue to be any animate or inanimate feature that individuals use to infer some meaning which can, in turn, be used to adjust future actions (Easterbrook, 1959; Hauser, 1996; Smith and Harper, 2003). In this regard, social cues are implicit or explicit behaviors (or their consequences) that allow an individual to infer some meaningful social information that can enhance the reliability of assessments of others' thoughts, feelings, and behaviors (Tanis and Postmes, 2003; Sauppé and Mutlu, 2014), These inferences, however, may also lead to social biases. Research has shown that social cues and biases are particularly interesting to research in IS usage contexts, such as e-commerce, technology adoption and recommender system use (Fleischmann et al., 2014). In these contexts, IS research has already provided important contributions on the phenomenon of nonrational decision-making (Fleischmann et al., 2014), but has left questions untouched on how social cues as digital nudges can shape user decision-making regarding, for example, investment amounts, information disclosure, and product choice. Thus, the leading research question of this thesis is:

RQ: How can social cues as digital nudges influence users in IS usage contexts?

To answer the question, five empirical studies on various social cues were published in four articles, applying numerous methodologies in several IS usage contexts.

1.2 Theoretical Foundations

This section begins with the presentation of dual process theory and the notion of heuristics to better understand the nature and emergence of cognitive biases. Subsequently, the section discusses the concept of digital nudging to explain the role of cognitive biases and their usage in digital choice environments. Lastly, the distinct category of social biases and the related role of social cues as digital nudges are presented to provide the reasoning for the positioning and the importance of the thesis.

1.2.1 Dual Process Theory, Heuristics and Cognitive Biases

Studies in behavioral economics, psychology and other related fields have demonstrated that individuals often behave irrationally and, thus, diverge from the classical concepts of human rationality (e.g., Simon, 1955; Kahnemann and Tverski, 1979). Dual process theory provides one explanation for the emergence of this irrational decision-making: The theory postulates that human beings comprehend reality in different ways (Epstein, 1994) and that they make use of two distinct processes to deal with information, often referred to as System 1 and System 2 (Welford, 1968; Stanovich and West, 2000):

System 1 is variously labeled as automatic, fast and largely unconscious to the individual. Conversely, System 2 is considered to be analytical, rational and slow. Numerous studies have investigated the two information processes (e.g., Djulbegovic et al., 2012; Dhar and Gorlin, 2013) and found that most activities in everyday life (e.g., routines) majorly involve only the intuitive System 1 (Kahneman, 2003; Kahneman, 2011) as these activities usually do not require the high cognitive effort of System 2. Instead, System 1 usually relies on heuristics (i.e., mental shortcuts) to reach decisions fast and efficiently with a moderate amount of information processing, thus reducing the cognitive load in decision-making. However, while these heuristics or “rules of thumb” (Hutchinson and Gigerenzer, 2005, p. 98) may be good for simple, recurrent tasks to reduce the amount of information and mental effort (Evans, 2006; Evans, 2008), they can cause systematic errors (i.e., cognitive biases) (Tversky and Kahneman, 1974) resulting in objectively irrational behavior by the individual.

According to Simon (1990), heuristics are a natural, rational adaptation to complex tasks that appropriately consider computational limits of the human being, thus being “methods for arriving at satisfactory solutions with modest amounts of computation” (p.11). Consequently, these satisfactory solutions are often right or appropriate, but sometimes result in biases when cognitive abilities limit the individual’s decision-making capacities, leading to inferior decisions (Haley and Stumpf, 1989). Consequently, cognitive biases are systematic errors in rationality and are thus inherent to human decision-making, in that System 1 often errs in the same direction and often results in similar errors based on the same biases (Dobelli, 2011).

1.2.2 Digital Nudging

Drawing on findings in behavioral economics, Thaler and Sunstein (2008) introduced the term nudging as a concept that addresses the design of choice environments to influence human behavior. Researchers found that choice environments and contexts can impact decision-making, such that the design in which options are presented can significantly influence individuals in their actions, even steering their behavior in predictable and desired ways. Accordingly, nudges are considered conscious interventions that are supposed to intentionally exploit or overcome human biases and heuristics in the immediate choice situations. Hereby, the idea of libertarian paternalism shapes the design and employment of nudges, such that designers of digital environments are legitimized to intentionally affect an individual’s behavior to reach a desired goal, while also respecting the individual’s freedom of choice (Sunstein and Thaler, 2003). Consequently, nudges are intended to benefit and act in the best interest of the decision-maker (Thaler and Sunstein, 2008). However, because there is no objectively neutral way to present choices, all decisions about the design of the choice environments affect user behavior, irrespective of the designer’s intention (Mandel and Johnson, 2002; Sunstein, 2015). Therefore, an imprudently designed choice environment may thus cause individuals to make undesired choices. Consequently, designers of these choice environments must understand the effect of their designs in order to foster positive effects (e.g., achieving desirable decisions) and reduce negative ones (e.g., decreasing freedom of choice).

Considering the development of the term nudge in recent years, Hansen (2016) defines the various facets of the concept in the following:

> *A nudge is a function of any attempt at influencing people’s judgment, choice or behavior in a predictable way, that is (1) made possible because of cognitive boundaries, biases, routines, and habits in individual and social decision-making posing barriers for people to perform rationally in their own self-declared interests, and which (2) works by making use of those boundaries, biases, routines, and habits as integral parts of such attempts. Thus a nudge amongst other things works independently of: (i) forbidding or adding any rationally relevant choice options, (ii) changing incentives, whether regarded in terms of time, trouble, social sanctions, economic and so forth, or (iii) the provision of factual information and rational argumentation. (p. 174)*

In other words, nudging inherently targets biases, either by leveraging or countering them, to influence the individual into a desired direction under some predefined prerequisites. Consequently, a nudge by definition always implies (1) an intent in the interest of the individual, (2) a bias (or related phenomenon) and (3) design constraints.

Whereas nudging was originally researched and applied in offline contexts, the increasing permeation of technology in various areas of private and professional lives requires the consideration and employment of nudges in digital choice environments. As a result, the concept of digital nudging was introduced to IS research to specifically deal with nudges that are unique to digital contexts. Precisely, digital nudging refers to the "use of user-interface design elements to guide people's behavior in digital choice environments" (Weinmann et al., 2016, p. 433). These design elements can take on various forms, such as making incentives more salient, preselecting an option by setting a default option, or providing user with feedback. While digital nudges, by definition, deal with decisions that are made in digital choice environments, their impact can reach out to real-world behavior (e.g., giving feedback in fitness apps). Moreover, the emergence of new contexts as well as the documentation of behavior (e.g., data mining) by means of digital advancement pave the way to potentially discovering new biases as well as analysing information processing, which have not been able to be examined or documented thus far.

In a scientometric analysis of top-rated publications in IS research, Fleischmann et al. (2014) found only 84 articles that had explicitly dealt with cognitive biases in the IS discipline between 1992 and 2012. Reviewing the AIS Senior Scholar's Basket of Journals (AIS, 2013) as well as ICIS, ECIS, Decision Support Systems and the International Journal of Electronic Commerce, I updated the scientometric analysis conducted by Fleischmann et al. (2014) and present the results in Figure 1-1. Moreover, since the publication of the catchword "digital nudging" (Weinmann et al., 2016), about half of published articles that directly refer to cognitive biases also explicitly address nudging. Therefore, one can derive from the data that there is a current trend in IS research that explicitly considers the well-being of decision-makers when analysing cognitive biases. Accordingly, this thesis intends to contribute to this current topic in research and focuses on digital nudges in IS with a specific focus on social biases and cues.

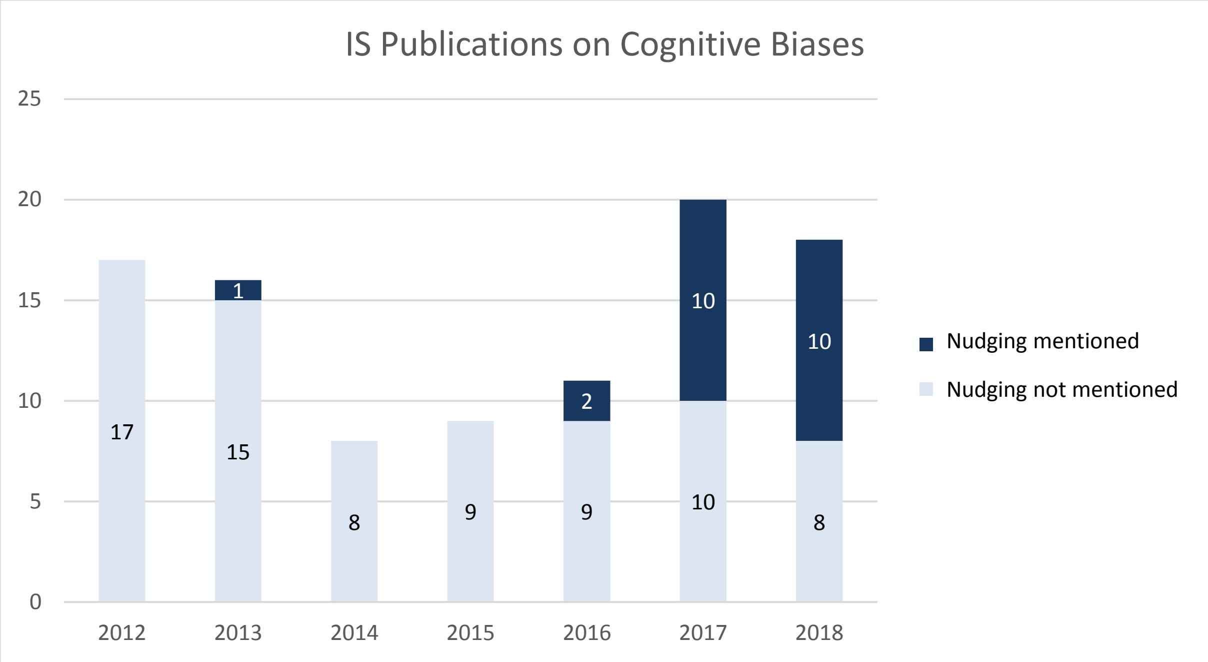


Figure 1-1: IS Articles on Cognitive Biases and Nudging (2012-2018)

1.2.3 Social Biases and Cues as Digital Nudges

Recently, cognitive biases from one especially interesting bias category has received particular attention: the social bias (e.g., Lamb and Kling, 2003; Goes, 2013; Pfeuffer et al., 2019). Social biases affect the perception of alternatives and arise from attitudes that are shaped by the decision-maker's relationship to other actors. The identified psychological effect underlying the social bias is the evolutionary social orientation of human beings (Blau, 2017). Individuals are prone to be influenced by social norms and the behavior of others, searching for social proof and indications of how to behave in a certain situation. Social norms are defined as "rules and standards that are understood by members of a group and that guide and/or constrain social behavior without the force of laws" and derive from "interaction with others; they may or may not be stated explicitly, and any sanctions for deviating from them come from social networks, not the legal system" (Cialdini and Trost, 1998, p. 152).

For a social bias to occur, the individual first must perceive a social cue that triggers the necessary heuristic. Drawing on human communication and cue utilization theory, in the thesis I consider a cue to be any animate or inanimate feature that individuals perceive and use to adjust their future actions (Easterbrook, 1959; Hauser, 1996; Smith and Harper, 2003). In this regard, social cues are implicit or explicit behaviors (or their consequences) that allow an individual to infer some meaningful social information that can enhance the reliability of assessments of others' thoughts, feelings and behaviors (Tanis and Postmes, 2003; Sauppé and Mutlu, 2014). Accordingly, although the application of a heuristic triggered by social cues may help in making a fast decision, the rather imprecise interpretation and usage of social cues sometimes lead to systematic errors, in that individuals make the same errors based on the same biases. For example, a product whose social cues indicate that it is sold frequently (i.e., social proof) is more likely to be bought by future customers (i.e., herd behavior or bandwagon effect) (e.g., Scharfstein and Stein, 1990; Van Herpen et al., 2009). This is because the provided cue signals the demand of previous customers, from which individuals infer information (e.g., popularity, desirability and value) about the product. If an individual, however, makes use of the social cue in his or her decision-making, the heuristic “well-sold product equals good product” may not be fully reliable, as the demand for that specific product could be irrelevant to the individual’s decision-making or linked to various reasons that are unrelated to the product’s attributes. Thus, a social bias that makes individuals strive to possess a good that other people already own may result in an inferior decision if incorrect or irrelevant information from the social cue is inferred and considered in the individual’s decision-making. Digital nudges, in this respect, can thus be employed to leverage or counter the social biases that originate in social cues.

Based on the aforementioned scientometric analyses in the previous sections, Table 1-1 provides an overview of the various kinds of social biases that have recently been investigated in the IS discipline. As can be seen, the number of publications per year as well the number of publications in total on social biases in IS research have increased when comparing Fleischmann et al.’s (2014) original analysis of a twenty-year period and the subsequent six years. Thus, the findings indicate a trend towards more research on social biases in IS. Yet, not all social biases have attracted an increase in attention (e.g., attribution error and cultural bias).

Social Biases	Articles (1992-2012)*	Articles (2013-2018)
Herding	Duan et al. (2009), Li and Hitt (2008), Wang and Greiner (2010)	Brandt and Neumann (2015), Burtch et al. (2018), Cheung et al. (2014), Dinev et al. (2015), Farivar et al. (2016), Gao et al. (2017), Hu and Lai (2013), Ma et al. (2013), Sun (2013), Zou et al. (2015)
Stereotyping	Clayton et al. (2012), Quesenberry and Trauth (2012)	Aerts et al. (2017), Dinev et al. (2015), Pahuja and Tan (2017)
Value Bias	Hosack (2007)	Glaser and Risius (2018)
Attribution Error	Rouse and Corbitt (2007)	
Cultural Bias	Burtch et al. (2012)	
	N = 8	N = 13

Note: * based on Fleischmann et al. (2014)

Table 1-1: IS Articles on Social Biases

Social biases can result from various social cues (see Table 1-2), and some social cues can be considered directly-traceable. These cues can be understood as conscious or unconscious triggers that are directly perceivable from a social actor and usually common and important for direct human-to-human interactions. For example, an individual’s perceptions of IS can be strongly influenced by the system’s displayed social cues. Here, research often differentiates between verbal (e.g., self-disclosure), nonverbal (e.g., message interactivity), and visual (e.g., avatar/embodiment) social cues. One phenomenon that can arise from these social cues is anthropomorphism, which describes the attribution of humanlike characteristics, behaviors and emotions to nonhuman agents (Epley et al., 2007; Pfeuffer et al., 2019). In human-human interactions, directly-traceable social cues can help in clarifying an individual’s meaning and intention, thereby reducing ambiguity in the communication. In human-computer interactions, these cues are usually used as digital nudges to anthropomorphize IS and, thus, to trigger social responses (e.g., treating computers like human beings) (Nass et al., 1994). Thus, IS designers leverage the positive benefits (e.g., social presence) (Qiu and Benbasat, 2009) of social biases through users’ impressions of social cues.

Besides directly-traceable social cues which can be immediately observed from a social actor, there are also indirectly-traceable social cues that result as a consequence of a social actor’s behavior, which still can trigger social biases that influence user decision-making. A common term and frequently used cue in this regard is social proof (e.g., indicating the number of people who have previously bought a product) (e.g., Cialdini, 1993; Amblee and Bui, 2012). Here, a further differentiation seems reasonable: In contrast to directly-traceable social cues, which more often emerge intentionally than unintentionally, indirectly-traceable social cues may happen either intentionally or unintentionally, dependent on the social actor's mental effort exerted in the situation. For instance, with regard to indirectly-traceable intentional social cues, customers who buy a product may intentionally leave a hint in the form of a social cue by creating a customer review or recommendation that can influence other customers in their purchase decision-making. On the other hand, with regard to indirectly-traceable unintentional social cues, customers may unintentionally affect other customers' purchase behaviors by neglecting how their purchase may influence the chances that the purchased product becomes a "bestseller" or sold-out.

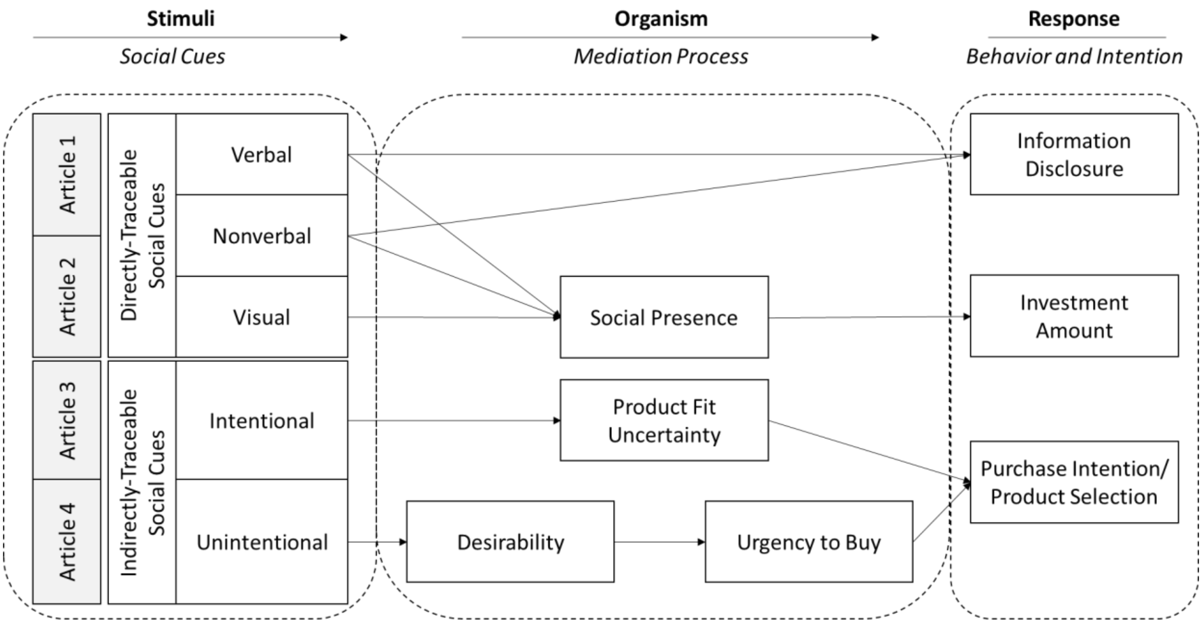
Social Cues				
Directly-Traceable			Indirectly-Traceable	
Verbal	Nonverbal	Visual	Intentional	Unintentional
e.g., self-disclosure, greeting and farewell	e.g., interactivity, typing indicators, response delay	e.g., avatar/ embodiment, animation	e.g., recommendations, posts	e.g., sold-out products, leftovers

Table 1-2: Categorization and Examples of Social Cues

1.3 Thesis Positioning

While research on cognitive bias has been conducted for more than 40 years in psychology and other related fields (Tversky and Kahneman, 1974), IS research has only recently started to consciously and explicitly call for studies that address the potential of the psychological concept (e.g., Browne and Parsons, 2012; Goes, 2013; Gupta et al., 2018). Many areas like IS usage contexts, still require deeper understanding of the individual's perceptions, the emergence and consequences of cognitive biases, and the employment of nudges when interacting and making decisions in digital choice environments. Specifically the social component deserves more attention (e.g., Lamb and Kling, 2003; Goes, 2013; Pfeuffer et al., 2019), which is also at the heart of IS discipline with its sociotechnical "axis of cohesion" that contributes to the distinctiveness and ability to coherently expand IS research's border (Sarker et al., 2019). To contribute to filling this gap, this thesis intends to showcase the variety and importance of social cues in IS usage contexts and is, therefore, to be understood as a first approach towards this understudied research branch. Furthermore, the results elucidate various underlying explanatory mechanisms of how and why biased decision-making takes place and how these mechanisms may be used to nudge users.

Drawing on the stimuli-organism-response (S-O-R) model in environmental psychology (Mehrabian and Russell, 1974), an appropriate framework for the various social cues as discussed in the articles can be derived to illustrate the focus and positioning of this thesis. According to the S-O-R paradigm, stimuli are cues external to the individual that attract the individual's attention (Belk, 1975) and can take on various forms (Jacoby, 2002) just like social cues. The organism corresponds to the intervening mediators between the stimuli and the responses, which comprise of perceptions, intentions and behaviors (Mehrabian and Russell, 1974). Various IS studies draw on the S-O-R model to explain an individual's decision-making processes and the resulting choice behavior (Xu et al., 2014; Amirpur and Benlian, 2015). As such, the S-O-R model serves as an adequate foundation to visualize and explain the connection between the analysed social cues (i.e., stimuli), the affected cognitive and affective processes (i.e., organism) and respective outcomes (i.e., responses). Figure 1-2 provides an overview of the articles' content embedded in the S-O-R model. In summary, the first two articles investigate how directly-traceable social cues can directly and indirectly (i.e., by increasing social presence) overcome technology usage hurdles (i.e., information disclosure and investment amount) in interaction with anthropomorphic IS, such as conversational agents and robo-advisors. The subsequent two articles deal with indirectly-traceable social cues, which take the form of either a recommendation (i.e., intentional cue) or a sold-out product (i.e., unintentional cue) and can affect purchase intention and product selection through a mediation of product fit uncertainty, desirability and/or urgency to buy.



Note: Interactions are not displayed to keep the illustration focused

Figure 1-2: Research Framework Including the Main Contents of the Research Articles

1.4 Structure of the Thesis

To answer the postulated research question, five empirical studies were conducted and published in four articles. This allows for the investigation of various social cues in different IS usage contexts while at the same time reaching sufficient depth to explore essential causal mechanisms with respect to their perceptions by and impacts on IS users. All studies were published in peer-reviewed scientific IS outlets. Subsequent to the introductory chapter about the motivation, research question, theoretical background and positioning of the thesis, the following four chapters present the four published articles, and a final chapter that concludes with contributions, limitations and directions for future research. The included articles were slightly adapted to achieve a consistent appearance throughout the thesis. Table 1-3 provides an overview of the chapters and articles.

Study 1	**Chapter 2** Article 1	**Conversational Agents in Affiliate Marketing** Adam, M. and J. Klumpe (2019). “Onboarding with a Chat – The Effects of Message Interactivity and Platform Self-Disclosure on User Disclosure Propensity,” In: *European Conference on Information Systems (ECIS).*
Study 2	**Chapter 3** Article 2	**Decision Support Systems in Financial Advisory Services** Adam, M., Toutaoui, J., Pfeuffer, N. and O. Hinz (2019). “Investment Decisions with Robo-Advisors: The Role of Anthropomorphism and Personalized Anchors in Recommendations,” In: *European Conference on Information Systems (ECIS).*
Study 3	**Chapter 4** Article 3	**Recommendations in Augmented Commerce** Adam, M. and M. Pecorelli (2018). “Recommendations in Augmented Reality Applications - the Effect of Customer Reviews and Seller Recommendations on Purchase Intention and Product Selection,” In: *European Conference on Information Systems (ECIS).*
Study 4/5	**Chapter 5** Article 4	**Sold-Out Products in Reward-Based Crowdfunding** Wessel, M., Adam, M. and A. Benlian (2019). “The Impact of Sold-Out Early Birds on Option Selection in Reward-Based Crowdfunding,” *Decision Support Systems*, 117(1), pp. 48-61.

Table 1-3: Overview of Articles

In the following, each of the four articles is briefly summarized regarding its procedure and main contribution regarding social cues as digital nudges. The articles will use the first-person plural (i.e., ‘we’), as multiple authors were involved in their creation.

- Article 1 (Chapter 2) provides insights on how social cues in conversational agents like chatbots can facilitate the user onboarding process. In cooperation with a German startup company, we empirically tested in a randomized field experiment how employing a nonverbal (i.e., message interactivity) and a verbal social cue (i.e., platform self-disclosure) in a conversational agent (i.e., chatbot) influence users to voluntarily self-disclose information in the form of their personal e-mail addresses. Moreover, the results reveal that the analysed social cues do not have individual effects, but in fact mutually enhance each other.

- Article 2 (Chapter 3) addresses the application of various directly-traceable social cues (e.g., picture of a human avatar) as well as the role of personalized recommendations in financial advisory services to increase investment volumes and thus enhance investors' finances by countering hyperbolic discounting bias. The results of the randomized online experiment demonstrate that not only directly-traceable social cues but also explicit recommendations can increase a user's perceived social presence during the interaction, which in turn influences potential investors to invest higher amounts.
- Article 3 (Chapter 4) continues with recommendations as social cues, but is specifically devoted to analyse whether the source of the recommendation (i.e., seller or other customers) influences the acceptance of product recommendations in augmented reality applications. The results of a randomized online experiment find that customer's recommendation (i.e., star ratings) may lead to a social bias and thus reduce the perceived fit uncertainty of a product for a potential customer, resulting in the selection of a product that previous customers recommended. However, the experiment also shows that customers refrain from adhering to a recommendation that is provided by recommendation system despite recent technological advances that allow these systems to potentially provide even more personalized and suitable recommendations for the individual customer.
- Article 4 (Chapter 5) examines the impact of displaying sold-out products in reward-based crowdfunding, thus providing valuable information for project creators for the design of reward option menus as well as findings on how potential backers make use of sold-out products as social cues to derive information from previous backing behavior. Based on a multi-method approach that comprised of a randomized online experiment as well as a longitudinal observational study, the results show that sold-out options do not have an impact on their own, rather, their effect is connected to and influenced by others factors in the environment, namely discount amount and the number of backers (i.e., another social cue).

Additional Articles (not included in the thesis):

In addition to the publications listed above, the following articles were also published during my time as a Ph.D. candidate. These articles are, however, not part of the thesis:

Adam, M., Wessel, M., and A. Benlian (2018). "Of Early Birds and Phantoms: How Sold-Out Discounts Impact Entrepreneurial Success in Reward-Based Crowdfunding," *Review of Managerial Science,* 1-16.[1]

Davcheva, E., Adam, M. and A. Benlian (2019). "User Dynamics in Mental Health Forums - A Sentiment Analysis Perspective," *Internationale Tagung Wirtschaftsinformatik.*

[1] This piece of research has received a best paper award

Chapter 2: Conversational Agents in Affiliate Marketing

Title: Onboarding with a Chat – The Effects of Message Interactivity and Platform Self-Disclosure on User Disclosure Propensity (2019)

Authors: Martin Adam, Technische Universität Darmstadt, Germany
Johannes Klumpe, Technische Universität Darmstadt, Germany

Published in: European Conference on Information Systems (ECIS 2019), Stockholm-Uppsala, Sweden.

Abstract

Activating users on online platforms is a critical endeavor that requires the employment of adequate user onboarding strategies, which focus on converting visitors into revenue-generating users. Despite a robust understanding of the antecedents of user onboarding behavior, researchers have devoted only little attention towards how platforms can actively influence desired user onboarding outcomes. Drawing on social response as well as social exchange theory, this study examines how disembodied interfaces like chatbots can facilitate the user onboarding process. In cooperation with a German startup company, we empirically tested in a randomized field experiment with 2095 visitors how low vs. high message interactivity (i.e., static vs. conversational presentation of requests) and platform self-disclosure (i.e., a platform providing information about itself) affect user disclosure propensity (i.e., likelihood that a user discloses information). Our results demonstrate that users in high message interaction conditions were significantly more likely to self-disclose in contrast to low message interaction conditions, while platform self-disclosure had a significant positive effect as well. Furthermore, high message interactivity significantly amplified the effect of platform self-disclosure on user disclosure propensity in contrast to low message interactivity. Consequently, our study provides novel findings on the effectiveness of disembodied interfaces to improve user onboarding behavior.

Keywords: Human-Computer-Interaction, User Onboarding, Chatbot, Message Interactivity, Social Exchange, Information Disclosure

2.1 Introduction

Nowadays, platform providers heavily struggle to turn visitors who reach their website into revenue-generating users. In fact, 96% of all website visits do not conclude in a purchase (Statista, 2018), and less than 25 percent of new app users return the day after the first use (Grennan, 2016). One of the reasons for this failure is that platforms face visitors with increasing privacy concerns and fears of privacy invasions due to platforms' tendencies to amass, process, and exploit users' personal data. Several studies in information systems (IS) have demonstrated that privacy concerns can thus hinder the willingness to accept new technologies (Angst and Agarwal, 2009), engage in e-commerce (Dinev and Hart, 2006), and disclose personal information (Lu et al., 2004). User onboarding strategies can address these challenges and assist visitors in overcoming their initial reservations by methodologically educating these visitors about a platform's digital products (i.e., onboarding) and thereby driving desirable business outcomes (e.g., user sign-ups and revenue generation) (Nielsen Holdings, 2013).

Conversational agents (CAs), such as chatbots, are "user interfaces that emulate human-to-human communication using natural language processing, machine learning, and artificial intelligence" (Schuetzler et al., 2018, p. 283). These technological artefacts are considered potential cost-effective solutions (e.g., Hopkins and Silverman, 2016; Oracle, 2016) and may define the future of user-provider interactions (e.g., Knight, 2016; Knijnenburg and Willemsen, 2016; Luger and Sellen, 2016). CAs have become especially important in customer service contexts (e.g., Gnewuch et al., 2017; Wünderlich and Paluch, 2017), where chatbots are of particular interest: For example, chatbots alone are expected to assist businesses in saving $8 billion per year in customer supporting costs by 2022 (Reddy, 2017). Thus, chatbots may pose strategic tools to facilitate user onboarding in various service encounters.

Although considerable research on the design of CAs has been conducted in IS, computer science, human-computer interaction (HCI), and adjacent fields, only few studies have tackled CAs in the context of user information disclosure success with regards to the design and incorporation of potential social cues (i.e., features that trigger social responses in individuals). Moreover, while prior studies on CAs have provided valuable contributions to research and practice (e.g., Hess et al., 2009; Qiu and Benbasat, 2009), their research primarily focused on embodied CAs that heavily rely on visual cues (e.g., physical embodiments). Yet, chatbots as disembodied CAs (Araujo, 2018) are considered significantly different from other CAs, as they influence user perception primarily through verbal (e.g., small talk) and nonverbal cues (e.g., blinking dots) (Seeger et al., 2018).

Accordingly, one of the prevailing questions that is still unfathomed is how message interactivity (i.e., the dependency of a message on another message) as a nonverbal cue influences user perception and behavior. More precisely, no study has compared how an interactive, conversational presentation of requests like in a human-human-interaction (i.e., a new question is only stated once the former question has been answered) impacts user onboarding behavior in contrast to a low interactive presentation of requests like in a classic form, in which all requests are presented at once in the beginning. Furthermore, although self-disclosure (i.e., process in which an actor self-discloses information to another person) has already proven impactful in face-to-face conversations (e.g., Collins and Miller, 1994), online user interactions in social media and forums (e.g., Barak and Gluck-Ofri, 2007; Lin and Utz, 2017), and conversations in HCI (e.g., Moon, 2000; Lee and Choi, 2017), this influence has not been investigated (1) in a field study to investigate actual user onboarding behavior, (2) in disembodied CAs that disclose information about their service platforms and not necessarily only about themselves, and (3) with regards to potential interactions with message interactivity. Indeed, both the underlying interactive design of chatbots and the reciprocal information disclosure are based on common human-human interactions where information is exchanged and revealed turn by turn and one after another. Thus, both cues are frequently used together in practice. Therefore, it is of utmost interest to analyse whether their underlying effects complement or substitute each other, as past studies have already indicated that different cues in CAs may interact surprisingly with one another (e.g., Seeger et al., 2018). The results of the investigation will provide learnings for both research and practice about the effects of employing these social cues and whether there is a benefit of using them together. Thus, to fill this gap, we raise the research question:

RQ*: How do message interactivity and platform self-disclosure – in isolation and in combination affect user onboarding behavior?*

To answer this question, we conducted an online field experiment with 2095 participants in cooperation with a German startup company. Precisely, we empirically validated how message interactivity and platform self-disclosure, in isolation and in combination, affect user onboarding behavior at the example of user disclosure propensity (i.e., the likelihood that a user discloses information).

In doing so, we intend to contribute to research and practice in several important ways. First, following the call for increased research on the design of CAs (e.g., Gnewuch et al., 2017; Seeger et al., 2018), our study departs from prior research by investigating the effects of a verbal and a nonverbal cue in disembodied CAs like chatbots, which have been neglected in past studies. Second, our piece of research intends to reveal an interplay between these two cues, which have not been scientifically investigated together, though their combination seems intriguing and may reveal surprising interactions (e.g., Seeger et al., 2018). Third and lastly, our endeavour also aims to provide actionable and generalizable recommendations for practitioners by highlighting how highly interactive conversational interfaces, such as chatbots, can have a positive impact on user onboarding behavior in contrast to classic static forms that are widely deployed today.

2.2 Theoretical Background

2.2.1 User Onboarding

User onboarding is “the sum of methods and elements helping a new user to become familiar with a digital product. By providing onboarding mechanisms, users will be enabled to smoothly pass into the efficient usage of the digital product” (Renz et al., 2014, p. 1). Consequently, enhanced onboarding can help users in better evaluating a platform’s products, while platform providers benefit from additionally generated revenues.

Facing the different stages of the conversion funnel (i.e., non-visitor, visitor, authenticated user, and converted customer) and the comparably high cost of user acquisition (i.e., turning non-visitors to visitors) (Gallo, 2014), platform and specifically app providers shift their attention towards increasing user activation outcomes (i.e., turning visitors into registered users) (Novak et al., 2003; Kireyev et al., 2016). Extant research has unveiled a psychological disposition of new users to underestimate the benefits of unfamiliar products or services during user activation (Gourville, 2006). That is why new users need to understand a product’s scope and concept rapidly or they will churn away (Cooper et al., 2007). Consequently, user onboarding has become the most critical step in the user journey, as it assists users in understanding the value of the presented product as well as in convincing to capture it (Murphy, 2016).

Extant literature has investigated user onboarding mainly along two streams, namely organizational socialization and gamification: First, organizational socialization refers to utilizing user onboarding tactics to introduce new individuals to become members of an organization (Bauer and Erdogan, 2011). Second, gamification literature has investigated how game design elements can help in meaningfully engaging new users in HCIs (Liu et al., 2017). Albeit, these valuable contributions research has only recently started to investigate the concept of user onboarding to improve a new user’s success with a product or service. A focal point of this nascent research stream has been to cluster typical design patterns which are used to improve user onboarding (Renz et al., 2014) and to investigate the long-term effectiveness of user onboarding on users’ intentions to continuous use (Cardoso, 2017). Yet, despite tremendous efforts and research on antecedents of decision-making across the conversion funnel, actionable design recommendations to improve activation outcomes have received only little attention and are yet to be fathomed (Novak et al., 2003; Kireyev et al., 2016; Murphy, 2016).

2.2.2 Social Response Theory

Social response theory (Nass et al., 1994; Nass and Moon, 2000) constitutes that individuals tend to perceive HCIs as social encounters. Accordingly, individuals instinctively treat computers as social actors, even if they know that their counterpart is a mere computer. This inclination and the resulting social responses become even stronger the more social cues (i.e., features that are usually related to human behavior, such as language and turn-taking) the computers display (Nass et al., 1995; Moon and Nass, 1996). Thus, explicit and inexplicit rules that normally guide human-human-interactions and emerge from social norms (i.e., standards that are comprehended by members of a group and that guide social behavior) (Cialdini and Trost, 1998) can be transferred to HCI (Fogg and Nass, 1997; Nass et al., 1999).

Numerous studies in HCI have demonstrated how the employment of CAs as well as the implementation of a few social cues can improve desirable business outcomes, such as purchase intention and company perceptions (e.g., Hess et al., 2009; Qiu and Benbasat, 2009). Yet, most of this research focused on embodied CAs (Araujo, 2018) and neglected the newly establishing disembodied CAs like chatbots, which majorly employ and rely on verbal (e.g., small talk) and nonverbal cues (e.g., blinking dots), except for the normally static profile picture. Thus, though heavily applied in practice, disembodied CAs and their related cues are understudied in research (Araujo, 2018; Seeger et al., 2018).

2.2.3 Interactivity and Message Contingency

The term interactivity comprises “technological attributes of mediated environments that enable reciprocal communication or information exchange, which afford interaction between communication technology and users, or between users through technology” (Bucy and Tao, 2007). Web interactivity, in this regard, can be defined as “interactive features embedded on computer website interfaces that allow reciprocal user-to-system or user-to-user communication” (Yang and Shen, 2017).

Of the three distinct dimensions normally associated with web interactivity (i.e., modality, message, and source) (Sundar, 2012), message interactivity, which is defined as message contingency in that the “systems’ output is contingent upon the user’s output” (Guillory and Sundar, 2014), is most essential to the user interaction with chatbots and has been found to be particularly essential in two-way communications like chat rooms or between users and website systems (Tedesco, 2007; Jiang et al., 2010). In fact, the sequential turn-taking, also known as the "conversational ideal" (Sundar et al., 2016), is a core characteristic of human-human-interaction and could thus be considered a separate nonverbal social cue, which has so far been unreflectively employed in several HCIs and specifically CA interactions (e.g., Häubl and Trifts, 2000; Cole et al., 2003; Xu et al., 2010). Indeed, researchers have neglected a direct comparison of a turn-taking chatbot interaction with the chatbot interface-enabled alternative of showing all possible conversation turns at once, like it is abundantly done in common forms where all statements and inputs are revealed initially to the user.

2.2.4 Social Exchange Theory and Reciprocal Self-Disclosure

Social exchange theory suggests that individuals establish mutual obligatory exchange relationships with other parties that are kept and developed by adhering to reciprocity norms, whereby positive or negative actions cause obligations to respond with similar actions, so that behaviors are normally repaid in kind (e.g., Gouldner, 1960; Cropanzano and Mitchell, 2005; Blau, 2017). The term reciprocity refers to the pan-cultural norm to repay any favor (e.g., benefits, gifts, treatments) received by an individual from another person (Sprecher et al., 2013) and can be comprehended as the perception of give-and-take in interactions (Weiss and Tscheligi, 2013). Moreover, the rule of reciprocity is considered elemental in human behavior (Gouldner, 1960), so that reciprocity can assist in creating the illusion that an agent is realistic (Becker and Mark, 1999).

Self-disclosure refers to any personal information that a social actor reveals to a different social actor (e.g., Wheeless and Grotz, 1976; Collins and Miller, 1994). Self-disclosure is essential for developing and keeping a relationship and decreases uncertainty between two actors by providing a means for reciprocal exchange of information (Collins and Miller, 1994). Extant literature has investigated self-disclosure along two different information revealing outcomes. On the one hand, research has aimed to unveil how individuals can be driven to disclose their inner feelings and overcome response biases (i.e., tendencies for users to respond inaccurately) (Jiang et al., 2013; Wakefield, 2013). On the other hand, self-disclosure has been investigated as the disclosure of personal information during digital user journeys where users' privacy concerns are driven by the users' scrutiny towards the privacy practices of the information acquiring party (Lowry et al., 2011; Klumpe et al., 2019).

There is a significant body of literature that deals with self-disclosure and the dynamics associated with it. For instance, streams of research focused on social desirability bias (e.g., Fisher, 1993; Mick, 1996). Still other research has investigated the influence of interviewer variability (e.g., Bailar et al., 1977; Webster, 1996) or liking (e.g., Jiang et al., 2011; Kashian et al., 2017). Regarding CAs, researchers have analysed aspects such as socially desirable responding (Schuetzler et al., 2018) and demonstrated that individuals can develop a relationship with a computer through the process of reciprocity and self-disclosure (Moon, 2000; Lee and Choi, 2017). In our study, we depart from prior research by empirically investigating the power of reciprocal self-disclosure in a real user onboarding setting with a chatbot that reveals information about the platform and not necessarily about itself (e.g., Zimmer et al., 2010; Saffarizadeh et al., 2017), thus complementing prior research with actual user behavior in interactions with disembodied CAs.

2.3 Research Model and Hypothesis Development

As depicted in Figure 1, our research model examines the effects of high message interactivity (MI) and platform self-disclosure (PSD) on user disclosure propensity (H1/H2) as well as the role of MI in moderating the effect of PSD on user disclosure propensity (H3). Thus, we intend to investigate the isolated and combined effects of our chosen social cues.

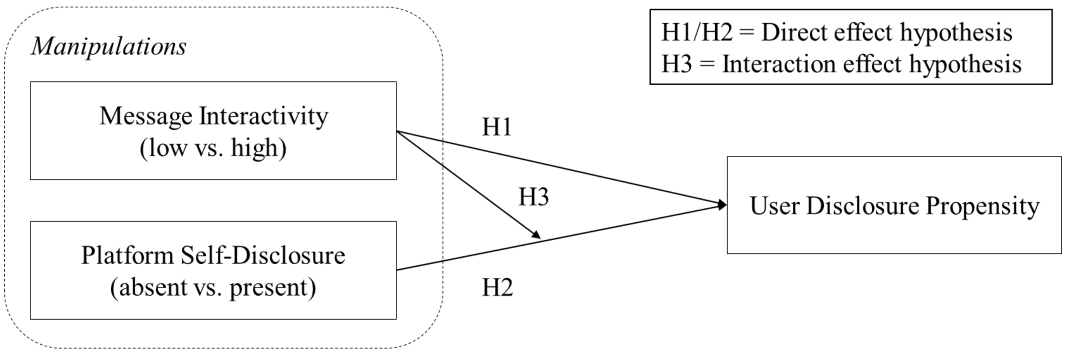


Figure 2-1: Research Model

2.3.1 The Effect of Message Interactivity on User Disclosure Propensity

As described earlier, we intend to investigate what will happen when the requests are low in message interactivity, so that all questions are presented at once at the beginning like in a classic computer form, in contrast to a high message interactive condition, when the questions are presented stepwise and conversational like in a dynamic dialogue. Social response theory (Nass and Moon, 2000) suggests that the more social cues are present, the more will a user perceive a CA as a social actor (Nass et al., 1994), making the user respond more socially. Thus, the conversational turn-taking in a high message interactive condition may improve the perception of the chatbot as a social actor in contrast to a low message interactive condition, as one more essential nonverbal social cue is included in the former.

Indeed, research has shown that interactivity is related to the perception of social presence which has been found in studies on CAs as well. For instance, Skalski and Tamborini (2007) demonstrated that perceived interactivity can influence social presence, information processing, and persuasion. Regarding social presence, research on embodied CAs revealed that it directly influences trusting beliefs, perceived enjoyment, and ultimately usage intentions (e.g., Hess et al., 2009; Qiu and Benbasat, 2009). Trusting beliefs, furthermore, were shown to influence privacy concerns as well as to increase user disclosure propensity (e.g., Smith et al., 2011; Taddei and Contena, 2013). Consequently, based on previous research on the positive effects of interactivity on business-oriented outcomes and related research on CAs that linked these effects to other outcomes on user behavior and intentions, we hypothesize that high (vs. low) message interactivity can increase user disclosure propensity.

H1: *High (vs. low) message interactivity will positively affect user disclosure propensity.*

2.3.2 The Effect of Platform Self-Disclosure on User Disclosure Propensity

A considerable amount of research has used social exchange theory to explain the reciprocation of favorable and unfavorable behaviors between parties (Cropanzano and Mitchell, 2005) and found disclosure reciprocity as a meaningful social norm in many social exchange contexts (e.g., Cropanzano and Mitchell, 2005; Sprecher et al., 2013). When two individuals encounter each other, the ability to build rapport is contingent on both parties to reciprocate in a dialogue (Collins and Miller, 1994; Sprecher et al., 2013). Normally, adhering to social norms improves the relationship, while violating hurts it (e.g., Collins and Miller, 1994; Sprecher et al., 2013). Consequently, if a party fails to reciprocate, the relationship will less likely have a positive development (Sprecher et al., 2013).

Applied to our experiment, social exchange theory suggests that if a platform gives away a piece of information, the user tends to respond by providing a piece of information of similar value to adhere to social norms. Indeed, past studies on website disclosure (e.g., "unreasoned dyadic relationships" defined as the platform discloses information first before asking for similar information) (e.g., Zimmer et al., 2010) have already indicated this reaction, in that a user may perceive an appropriate and non-manipulative self-disclosure as a rewarding outcome and a cue to build trust (Collins and Miller, 1994), hence appreciating the action (Emerson, 1976) and tending to mimic the behavior (Chartrand and Bargh, 1999). Actually, reciprocal self-disclosure may even pose such a strong social norm that even information disclosure by a computer may be considered a verbal social cue and can, thus, create the perception of a social actor (Nass et al., 1994). Consequently, platform self-disclosures may create feelings of imbalance in users that are usually only created in human-human-interactions. As a result, a user desires to restore equality in the relationship (Sprecher et al., 2013) and reestablish an equilibrium with the computer (Homans, 1958). Thus, we expect that the self-disclosure of the platform in a disembodied CA will cause the user to self-disclose information more likely.

H2: *Platform self-disclosure will positively affect user disclosure propensity.*

2.3.3 The Moderating Role of Message Interactivity on the Effect of Platform Self-Disclosure on User Disclosure Propensity

Previous research has shown that social cues may surprisingly interact with each other, increasing the perception of social presence and related dimensions (e.g., Seeger et al., 2018). Regarding the effects of our investigated cues, the high message interactivity condition with its sequential turn-taking as a nonverbal cue, also known as prerequisite of the "conversational ideal" (Sundar et al., 2016), may be so essential that other cues can develop their potentials more effectively in its presence. The verbal social cue self-disclosure may be a specifically intriguing candidate, as both cues are fundamental in common human-human interactions where information is exchanged and revealed turn by turn and one after another: Whereas high message interactivity is defined as one message is contingent on and only revealed after another message, reciprocal self-disclosure is built on the concept that one party starts to self-disclose so that the other party can socially respond by self-disclosing as well. Therefore, the perception of a give-and-take information exchange may flourish better when a user perceives a sequential turn-taking in form of high message interactivity, so that the user reasons that his or her self-disclosure has consequences on the conversation and, thus, on the relationship and following interaction between the user and the chatbot. Consequently, we believe that when both cues are presented together, they increase the chances that users will disclose information, in that high message interactivity enhances the effect of platform self-disclosure.

H3: *High message interactivity will moderate the effect of platform self-disclosures so that high message interactivity will enhance the effect of platform self-disclosures on user disclosure propensity.*

2.4 Research Methodology

2.4.1 Experimental Design and Procedure

We employed a 2 (MI: low vs. high) x 2 (PSD: absent vs. present) between-subject, full-factorial design to conduct both relative and absolute treatment comparisons and to isolate individual and interactive effects on information self-disclosure. The hypotheses were tested by means of a randomized field experiment in the context of a real online platform of a German startup company (www.die-masterarbeit.de) that provides a free matching service for students and companies based on interests in topics for university-related Master theses. We selected that startup company for three main reasons: First, startup companies usually lack an established customer base and are, therefore, highly dependent on acquiring new users. Second, startup companies find it usually hard to compete against and stand out from established companies and are, consequently, highly dependent on providing visible value and perceivable distinction, which can be amended by using new technologies such as CAs. Third, the startup company we worked with usually provides the service once to each of its active users, so improving user onboarding and convincing users to commit to related activities and products, such as newsletter signups and user referrals, is highly important for the company. For example, with the newsletter signups, the company cannot only inform users about new topics and lure them back to the website, but it can also generate revenues by placing advertisement in its newsletters.

In our field study, the instant messaging interface was self-designed and asked in all conditions for textual input. Consistent with previous studies and often applied in practice (e.g., Burger, 1999), we used the foot-in-the-door technique in all conditions in form of a continued-questions procedure in a same-requester/no-delay situation (see Figure 2): (1) First, a new website visitor was randomly assigned to one of the four conditions and (2) shown an instant messaging interface as a pop-up in which the interface introduced itself to assist the user in finding a topic for a potential thesis according to the user's interest. If the user did not want to use the interface, the user could easily just close the pop-up at the beginning or during the interaction with the interface and continue on the page. If the user decided to use the interface, he or she saw the design and content of the interface based on the condition that was assigned. (3) In all conditions, three questions about thesis- and company-relevant information (i.e., degree, major, and desired state of the company to be located) was asked first, which represented rather insensitive data of the user, since the given information applies to various people but still created involvement as participants had to answer them completely and truthfully to proceed and end up with personalized recommendations that fit to them. (4) Subsequently, depending on the condition and manipulation, the platform self-disclosed information through the interface by providing its service e-mail address or presented a filler that did not contain any self-disclosure (see next section). (5) Afterwards, we placed our target request, which was one question about a potential newsletter sign-up, in which users had to respond with their personal e-mail addresses, if they wanted to sign-up. Otherwise the user left the field empty. Consequently, the target request was more sensitive since it asked for more intimate and user-unique information. (6) To proceed to the topics for a potential thesis, the user eventually clicked on a button and was sent to a different page with topics that were filtered based on the user's entries.

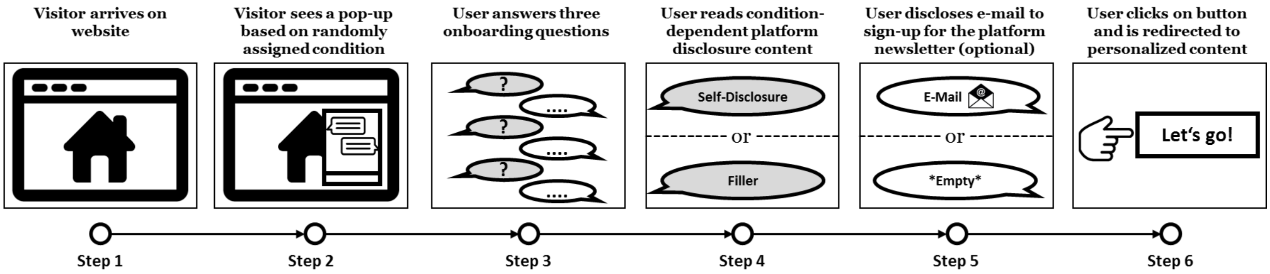
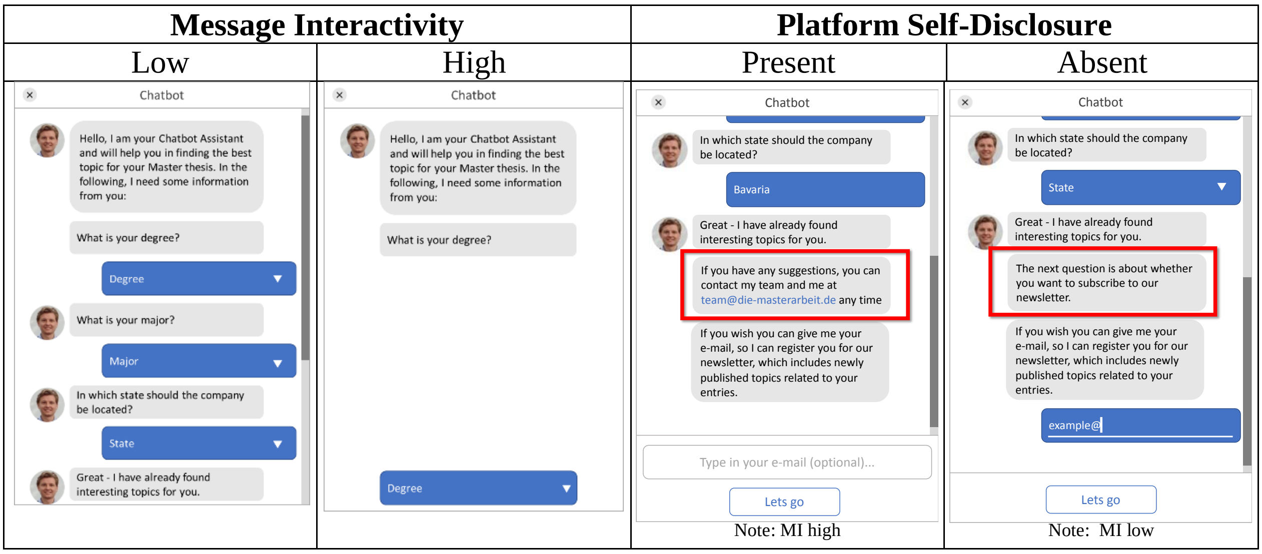


Figure 2-2: Experimental Procedure

2.4.2 Manipulation of Independent Variables

Consistent with previous research on MI (e.g., Jiang et al., 2010), we defined and manipulated MI as either low or high. In the low MI condition, all questions were shown at once in the beginning, so that a user immediately saw how many questions he or she had to answer to proceed to the next page. In contrast, the high MI condition presented the questions one after another, so that the user could see only one question at a time and proceed only if he or she answered the question. The questions in both conditions could be answered through one of two predefined kinds of input fields, which are often applied in chatbots in practice: (1) The user could answer the first three questions by selecting one of the predefined answers in a drop-down list, as the website required a certain degree of input control to further process user input in its user-thesis-matchmaking. (2) The user could answer the target question about a potential newsletter sign-up with his or her e-mail address in a free text input field (i.e., "Type in your e-mail (optional)…"). In the low MI condition, the input fields were located where the user's responses would normally be placed in a chat record. In the high MI condition, the input fields where placed at the bottom of the interface where they are usually displayed in turn-by-turn chatbot interactions (see Figure 3).

The target question, whether the user wants to sign-up for the newsletter with his or her e-mail address, was preceded by a statement that was dependent on the presence or absence of the PSD. In accordance with past experiments on reciprocal interactions with computers (e.g., Moon, 2000), the platform first self-disclosed in the PSD present condition by providing its service e-mail address through the interface before asking the user for his or her e-mail address. Thus, we depart from prior limited research on disembodied CA self-disclosure (Lee and Choi, 2017; Saffarizadeh et al., 2017) by focusing on platform-related self-disclosure through the chatbot. Precisely, consistent with previous research (e.g., "We can be contacted at jmeyer@webmd.com" (Zimmer et al., 2010, p. 404)), we operationalized PSD in that the chatbot revealed information about the platform's customer service and not directly about itself: The chatbot provides a service e-mail address for further customer support and not a private one (i.e., "In case you have any suggestions, feel free to contact my team and me at team@die-masterarbeit.de any time.”). In doing so, we manipulated PSD as a piece of information that an automated first-level support in practice could provide to assist the user if the user requires human second-level support. In the PSD absent condition, to avoid confounding effects such as questions length (e.g., Koomen and Dijkstra, 1975), we followed Moon (2000) and showed a statement that did not contain any computer-disclosure content, but contained the same number of words as in the PSD present (untranslated) condition.



Note: The left two columns exemplify that whereas in the low MI all questions are displayed in the beginning at once, in the high MI the next question is displayed only once the user has answered the preceded question. The right two columns illustrate how the interface output changes dependent on the presence (i.e., service e-mail address displayed) or absence (i.e., not displayed) of the PSD.

Figure 2-3: Translated Excerpts from the Experimental Conditions

We developed our stimuli and evaluated the success of our manipulations by replicating the experimental design and conducting a pretest in form of an online experiment, involving 160 students (mean age = 23; 63% male) who we recruited via Facebook. Students were intentionally chosen as they would represent the customer group that would also visit the start-up website. We incentivized participation through a voluntary raffle of three Euro 20 vouchers for Amazon and exposed each participant to one of the four aforementioned conditions. Instead of user disclosure propensity, we measured Social Presence (Gefen and Straub, 2003) in a post-experimental questionnaire, as this variable has demonstrated to be essentially related to social cues (e.g, Qiu and Benbasat, 2009) as well as interactivity (e.g., Skalski and Tamborini, 2007). Indeed, participants perceived greater Social Presence when they were exposed to a high MI ($M = 3.45$; $StD = 1.37$) compared to when they were exposed to a low MI ($M = 2.71$; $StD = 1.46$; $F(1,159) = 11.16$; $p < 0.01$). Likewise, participants that encountered PSD perceived greater Social Presence ($M = 3.33$; $StD = 1.39$) than when PSD was absent ($M = 2.79$; $StD =$

1.49; F(1,159) = 5.65; $p < 0.05$). Consequently, the results of our pretest indicated that our manipulations should also be successful on the real platform.

2.4.3 Dependent Variable and Control Variables

We measured user disclosure propensity based on a binary variable, defined as a point estimator P :

$$P \quad (\text{user disclosure propensity}) = \frac{\sum_{k=1}^{n} x_k}{n}$$

where n denotes the total number of unique new website visitors in the respective condition who finished the interaction (i.e., answering all three mandatory questions and hitting the proceed button) and x_k is a binary variable which equals 1 when the user self-disclosed by inserting an e-mail address and 0 if not. Furthermore, in case the user provided his or her e-mail address, an e-mail was sent to the mentioned address to verify and confirm the active usage of that e-mail address by the user.

Moreover, we also checked for various control variables: First, we measured whether users used a mobile device to visit the website. Second, we recorded the day the user participated in the experiment. Lastly, we measured the total time of the session duration that the user needed to complete the journey.

2.5 Results

2.5.1 Sample Description and Control Variables

We recorded all our variables via clickstream analysis over a 30-day period in March and April 2018. From 2095 visitors with a unique IP address, 202 used the interface till the end (8.4% conversion rate). We eliminated 26 subjects that disclosed false e-mail addresses, resulting in a sample size of 176 subjects (see Table 1, Table 2). Regarding our dependent variable disclosure propensity, the distribution of disclosures across the experimental groups was as follows: In conditions where MI was low, disclosure propensity was 15% when PSD was absent and 26% in the presence of PSD. While in conditions where MI was high, disclosure propensity was 19% when PSD was absent and 68% in the presence of PSD.

	Total	Low MI x PSD absent	High MI x PSD absent	Low MI x PSD present	High MI x PSD present
Participants	2095	523	501	569	502
Mobile Usage	1617	394	400	440	383
Submitted	202	46	40	53	63

Table 2-1: Descriptive Statistics of Website Visitors

	Mean	SD
Dependent Variable		
Disclosure Propensity	0.27	
Independent Variables & Controls		
MI (low=0, high=1)	0.38	
PSD (absent=0, present=1)	0.52	
Mobile Usage	0.98	
Experiment Day (days)	13.07	7.882
Duration of Session (seconds)	44.06	23.795

Table 2-2: Descriptive Statistics of Analysed Data Set

In order to confirm the randomized assignment of the participants to the experimental conditions, we conducted several one-way ANOVAs. We found no statistically significant difference in mobile usage ($F = 0.628$; $p > 0.05$), day of the experiment ($F = 0.437$; $p > 0.05$), and session duration ($F = 0.446$; $p > 0.05$) between all experimental groups, which confirmed that the randomization was successful.

2.5.2 Main Effect Analyses for MI and PSD

To test H1 and H2, we conducted a three-stage hierarchical logistic regression on the dependent variable user disclosure propensity. First, we included all control variables (Stage 1), then we added the independent variables MI and PSD (Stage 2), and lastly we inserted the interaction term of MI x PSD (Stage 3). Our results showed that both MI and PSD significantly affected user disclosure propensity (see Table 3).

Supporting H1 and H2, the binary logistical regression in Stage 2 demonstrated a statistically significant main effect for MI ($b = 1.830$; Wald statistic (1) = 18.867; $p < 0.001$) and PSD ($b = 1.208$; Wald statistic (1) = 8.707; $p < 0.01$). More precisely, users in the high MI have 6.24 times higher odds to self-disclose compared to the low MI, while users in the PSD present condition have 3.35 times higher odds compared to the absent PSD conditions. Furthermore, the results of Stage 3 demonstrated a statistically significant positive interaction effect of MI and PSD on user disclosure propensity ($b = 1.766$; Wald statistic (1) = 4.889; $p < 0.05$), giving a first indication in support of our H3.

Intercept	Stage 1 Coeff	SE	Exp(B)	Stage 2 Coeff	SE	Exp(B)	Stage 3 Coeff	SE	Exp(B)
Constant	-2.091	1.431	.124	-4.438**	1.537	.012	-4.143**	1.572	.016
Manipulations									
MI †				1.830***	.421	6.235	.813	.593	2.256
PSD ††				1.208**	.409	3.345	.272	.555	1.312
MI x PSD							1.766*	.799	5.846
Controls									
Mobile Usage	.407	1.325	1.503	.705	1.315	2.025	1.066	1.376	2.904
Experiment Day	-.018	.023	.982	-.008	.026	.992	-.010	.026	.990
Duration of Session	.020**	.007	1.021	.029***	.008	1.029	.029***	.008	1.030
Nagelkerke's R^2	.074			.265			.297		
-2 (Log-Likelihood)	197.001			170.701			165.812		
Omnibus-Tests	9.255*			35.554***			40.443***		

*Note: N = 176; * p < 0.05; ** p < 0.01; *** p < 0.001; SE= Standard Error, Coeff = Coefficient;*
† low=0, high=1; †† absent=0, present=1

Table 2-3: Binary Logistic Regression on User Disclosure Propensity

2.5.3 Interaction Effect Analysis for MI and PSD

We suggest in H3, that MI will moderate the effect of PSD on user disclosure propensity. Our binary logistic regression has already indicated this moderation effect. Thus, we conducted a bootstrap moderation analysis with 10,000 samples and a 95% bias-corrected confidence interval to test whether MI moderates the effect of PSD (Hayes, 2017, model 1). The results of our moderation analysis show that the effect of PSD on user disclosure propensity is moderated by MI such that the effect is enhanced when MI is high (effect = 2.579, standard error = 0.559) compared to when MI is low (effect = 0.813, standard error = 0.593). Furthermore, the analysis unveiled that the effect of PSD is only statistically significant in presence of high MI (95% bias-corrected confidence interval (CI) = [1.483, 3.675]) but not when low (95% bias-corrected confidence interval (CI) = [-0.349, 1.976]). To compare the interaction effect with the individual factors, we conducted a simple slope analysis (see Figure 4). The effect of PSD on user disclosure propensity in the high MI condition is higher (24.54%) than the effect of low MI on user disclosure propensity when MI is low (15.91%). On the other hand, the isolated effects are each outperformed when both manipulations are employed together (71.39%).

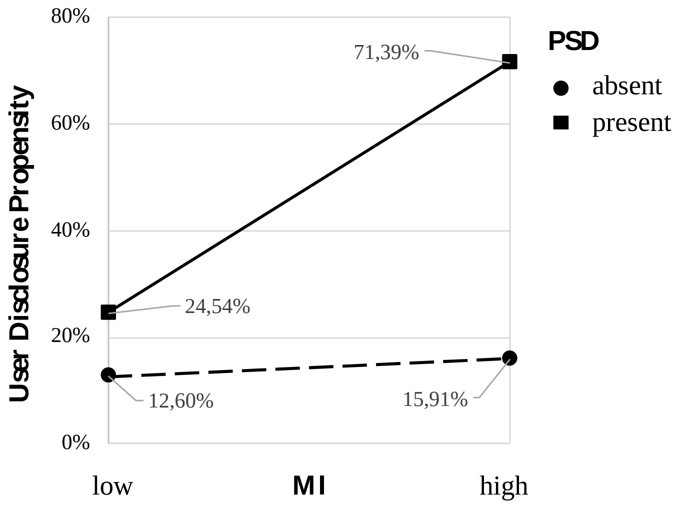


Figure 2-4: Simple Slope Moderation Analysis

2.6 Discussion and Implications

E-commerce has been experiencing dramatic growth over the past decade and online competition has becoming fiercer for online platforms. As a result, potential users are overwhelmed with offers and information of various providers, leading to small conversion rates and increased churn rates. Consequently, providers have to come up with better onboarding strategies to convert mere visitors to revenue-generating users. CAs, such as chatbots, have been becoming popular in various customer service settings and are considered potential strategic tools to facilitate the user onboarding process.

Our empirical investigation examined how platforms can employ a chatbot with different social cues in their user onboarding strategy to positively influence user disclosure propensity. Specifically, we analysed how the nonverbal cue MI and the verbal cue PSD used in an instant messenger interface on a real online platform affects user information disclosure in form of newsletter sign-ups. Our results demonstrated that both independent variables had a distinct and significant impact, in that users in the high MI were more likely to self-disclose their e-mail addresses in contrast to the low MI, while users in the PSD present condition (in contrast to the PSD absent condition) were more likely to self-disclose as well. However, our results showed a statistically significant positive interaction effect of MI and PSD on user disclosure propensity, in that the effects could be observed only when both cues were present.

This research contributes to IS in three important ways. First, following the call for a more actionable research on the design of CAs (e.g., Gnewuch et al., 2017; Seeger et al., 2018), our piece of research extends prior research by addressing disembodied CAs like chatbots, which have been neglected in past studies. More specifically, we investigated the effects of one nonverbal (i.e., message interactivity) and one verbal cue (i.e., self-disclosure), which are understudied yet widely applied in practice. Most importantly, our findings speak to the psychological importance of message interactivity: We analysed the effect of visualized turn-taking, which before has been unreflectively and abundantly applied in chatbots both in research and practice, neglecting an examination of the fundamental nonverbal cue for the "conversation ideal" (Sundar et al., 2016) on its own. Moreover, we depart from prior research on computer self-disclosure that profoundly investigated website self-disclosure (e.g., Zimmer et al., 2010) and particularly CA self-disclosure (e.g., Lee and Choi, 2017) by having a more practice-oriented approach: Whereas past studies on CAs primarily investigated self-disclosure as a piece of information that is directly related to the social actor (e.g., providing information about the CA's own identity or feelings) (e.g., Moon, 2000; Saffarizadeh et al., 2017), we investigate platform self-disclosure in that the chatbot reveals primarily information about the platform and the platform's (human) customer service (Zimmer et al., 2010) and not directly about itself.

Second, our study addressed an interplay between the analysed cues, which seems especially worthwhile due to recent surprising findings on the combination of different cues (e.g., Seeger et al., 2018). This interplay of our cues has not been investigated in disembodied CAs before, though a combination seemed particularly intriguing as both cues are fundamental in human-human interactions where information is exchanged turn by turn and one after another. It seems that the nonverbal cue of message interactivity is so essential that other cues, such as self-disclosure, can develop their effect only or at least better when a user perceives a certain degree of message interactivity. Thus, our results indicate, also in a broader context, that studies on information disclosure need to consider the degree of (message) interactivity to correctly interpret the resulting disclosure effects (e.g., Weisband and Kiesler, 1996; Chu and Kim, 2017).

Third and lastly, we provide findings on actual user onboarding behavior. Precisely, our sample consisted of real visitors who intentionally and self-motivated entered a website and who voluntarily and out of self-interest provided their e-mail addresses to become registered users. This procedure is unprecedented in contrast to previous studies that were limited to laboratory experiments and user intentions. Moreover, instead of creating a complex personality for the CA (e.g., Holzwarth et al., 2006), which has been shown to even create negative reactions in some settings (e.g., Mimoun et al., 2012), we kept the chatbot simple, generalizable, and easily implementable for service-oriented purposes of practitioners. Consequently, we deliver actionable recommendations as well, in that these findings help providers in their decision-making to use and design highly interactive formats like chatbots if they desire better user onboarding outcomes in contrast, for instance, to plentifully employed, but lowly interactive forms.

2.7 Limitations and Directions for Future Research

The conducted study should be treated as an initial empirical investigation into the realm of disembodied CAs and onboarding strategies and, thus, needs to be understood with respect to some noteworthy limitations which at the same time represent opportunities for future research. First, although we carefully designed our experiment, we could not fully control the website of the platform and check user characteristics. Potential confounding effects might have influenced our results, although a pretest ascertained internal validity for our manipulations. Future studies may try to replicate our field study on a platform with more control over potential confounds and even in an experiment to identify and measure potential effects of moderators, mediators, and other control variables quantitatively.

Second, in our study we investigated one specific design of message interactivity and self-disclosure on one particularly designed interface in one product category of one platform with respect to one onboarding outcome. Thus, we encourage future studies to test other forms of these cues and evaluate their effects in the same and other product categories and dependent variables, especially with regard to revealed interaction effect of our analysed manipulations. It would be interesting to see in future HCI studies, how these cues will perform in product categories with higher involvement (e.g., car and camera purchases) (Aggarwal et al., 2007), in more sensitive privacy disclosure environments (e.g., health care or recruiting) (e.g., Sah and Peng, 2015; Schuetzler et al., 2018), and in combination with other cues (Seeger et al., 2018). The investigation of adjustments and variations in our experimental design, such as number of questions and number of self-disclosures, could also be a worthwhile endeavor. Moreover, other dependent variables, such as purchase behavior and user referral, may also be examined.

Third and lastly, researchers and practitioners should be careful with our results, as the phenomenon of disembodied CAs is quite new in practice. Only recently chatbots have sparked great interest in companies (Knight, 2016; Luger and Sellen, 2016). Users may get familiar with the presented cues and will adjust their behavior over time, once they get accustomed with the new technology.

Chapter 3: Decision Support Systems in Financial Advisory Services

Title: Investment Decisions with Robo-Advisors: The Role of Anthropomorphism and Personalized Anchors in Recommendations (2019)

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Abstract

The current wave of digitalization forces companies to adapt their offline activities to meet contemporary customer expectations and technological possibilities. One current challenge for the financial services sector is to shift its traditional, in-person advisory process into a digital, automated service (i.e., robo-advisory) to reduce costs as well as to reach a wider audience of prospective customers. By neglecting to increase and invest their savings, customers run the risk of making suboptimal economic decisions that may negatively affect their economic futures. Drawing on social response as well as anchor-adjustment theory, we investigate anthropomorphism (i.e., the attribution of human characteristics and goals to non-human agents) and personalized anchors in recommendations as IS design elements in the context of robo-advisory for investment decisions. Our results from an online experiment with 278 participants show that anthropomorphism (i.e., triggered by verbal and visual cues) and personalized anchors in recommendations lead to higher social presence which in turn lead to increased investment volumes. Additionally, we demonstrate that personalized anchors in recommendations directly increase investment volume. Thus, our results contribute by providing novel findings on how anthropomorphism and personalized anchors in recommendations can be used to improve economic decision-making.

Keywords: Robo-Advisory, Nudging, Anthropomorphism, Anchor, Online Recommender Systems, Financial Support Systems

3.1 Introduction

Digitalization is a significant topic that is no longer dispensable. Caused by an increasing infusion of information systems (IS) into everyday activities and the rise of ubiquitous technologies, digitalization has an impact in various areas in economy and society, of which the financial services industry is no exception (Alt and Puschmann, 2016).

As a result, new financial services, such as “robo-advisory,” have emerged. Robo-advisors are IS that guide users through an automated investment advisory process by means of interactive and intelligent user support components (Sironi, 2016; Jung et al., 2018). Consequently, robo-advisory allows a larger audience to access and use a professional asset management at low costs, which before has been affordable by only wealthy investors who could pay costly human advisors (Jung et al., 2018). Indeed, A.T. Kearney estimates that assets under management by U.S. robo-advisors alone will grow to 2.2 trillion dollars by the end of 2020 (A.T. Kearney, 2015).

Because digital services replace the traditional human-to-human interaction between human advisors and their customers, one challenge that financial service companies face is the design of adequate robo-advisory services that are accepted by potential investors (Jung et al., 2017). Yet, little is known on how the design and mechanics of robo-advisory can improve economic decision making. Today’s customers might not save enough money for their future (Skinner, 2007), often being influenced by heuristics in their economic decision-making (Fleischmann et al., 2014), leading to biases against saving (Benartzi and Thaler, 2007). In offline contexts, several nudges have already demonstrated to improve the economic decision-making of customers regarding their saving and investment decisions (e.g., Cronqvist and Thaler, 2004; Thaler and Sunstein, 2008). However, online contexts such as robo-advisory may open the opportunity for new approaches to further improve economic decision-making.

Robo-advisory is a phenomenon that is still in its infancy in finance and IS, so that only few researchers have devoted their attention to this support system. Recent robo-advisory research draws on foundations from related fields, such as the development of portable advisory tools (Moewes et al., 2011; Heinrich et al., 2014) and the design of financial encounters (Dolata and Schwabe, 2016) to increase comprehension and success with regard to the configuration and profiling of users in form of user investment behavior (Kilic et al., 2015; Musto et al., 2015) and the design of user interfaces to improve user experience (e.g., Nueesch et al., 2014; Heyman and Artman, 2015). An important theory for forming a more natural bond between the user and the system may be found within anthropomorphism. Anthropomorphism leads humans to attribute human characteristics and intentions towards non-human agents (Epley et al., 2007), resulting in social behavior even with non-human agents. Although anthropomorphism has been a topic of interest for scant research works in IS (e.g., Qiu and Benbasat, 2009; Qiu and Benbasat, 2010) and has even been researched in the context of robo-advisors by employing a simple name (Hodge et al., 2018), no study has yet explored the usage of anthropomorphism in the form of visual and verbal cues to increase investment volumes. Such visual and verbal cues have been proven to be decisive design elements in other fields like marketing and researchers have provided evidence that these cues can positively impact product likeability and product purchase intention (e.g., Holzwarth et al., 2006) and promise even more fruitful ventures in the future (Seymour et al., 2018). Based on such previous research findings, Pfeuffer et al. (2019) argue that the conventionally personal consultation talks between investor and investment advisor call for a more natural design of the human-computer interaction in robo-advisory. Therefore, it appears logical that employing an anthropomorphic conversational recommendation agent may lead to a higher efficiency of robo-advisory. Moreover, the emergence of robo-advisors as real-time recommender systems also raises questions with regard to how the provision of fast and personalized recommendations based on user input further shapes investors' investment decisions. Thus, this paper aims to investigate the following research questions:

RQ1*: How does anthropomorphism in robo-advisors affect investors' investment volumes?*

RQ2*: How do personalized recommendations in robo-advisors affect investors' investment volumes?*

To answer our research questions, we employed an online experiment with 278 participants in a 3 (Anthropomorphism: Absent vs. Low vs. High) x 2 (Personalized Recommendation: Absent vs. Present) between-subject design and systematically analysed the first steps in a robo-advisory onboarding process and assessed the intended investment volumes. Consequently, we examined the impact of anthropomorphism, manipulated by verbal and visual design elements, as well as of personalized recommendations, operationalized through a user-input dependent numerical anchor in a recommendation by the robo-advisor. In doing so, we contribute to IS research and practice in several important ways. First, following the emergence and important growth of robo-advisory (A.T. Kearney, 2015; Jung et al., 2018) we address the theoretically and practically neglected effects of anthropomorphism and personalized recommendations as effective nudges in the newly emerging robo-advisory context. Second, we provide an explanation for these observations through the mediating effect of social presence, which is built upon the general bias towards social orientation of human being (Nass and Moon, 2000). Third, we depart from prior research by investigating how these influences improve economic decision-making like investment and savings behavior. Lastly, we show the possibility of IS to provide real-time personalization in a financial context that would not be possible in a traditional offline setting. Thus, we not only shed theoretical light on our investigated effects, but also derive learnings for providers of financial services to increase investment volumes to improve economic welfare.

3.2 Theoretical Background

3.2.1 Robo-Advisors and Recommendations

Robo-advisors as financial support systems provide financial advice to potential investors based on algorithms that analyse financial information with less human intervention than ever before (Jung et al., 2017; Jung et al., 2018). As a result, robo-advisors challenge the traditional fund and wealth management industry (Phoon and Koh, 2017). Robo-advisors have several important applications, and depart from existing services (e.g., online investment platforms and online brokerage) with regard to customer assessment and customer portfolio management (e.g., Tertilt and Scholz, 2017; Jung et al., 2018): The traditional investor profiling that is normally conducted during offline human-to-human interviews is replaced by online questionnaires and self-reporting processes. Therefore, the user-provided answers (e.g., with regard to investment purpose or risk affinity) are used as inputs for algorithms and automated processes, instead of being processed by human advisors. Subsequently, the robo-advisor translates this information in real-time into an adequate portfolio of financial products, provides users with personalized recommendations as well as automatically manages the investment portfolio.

Previous research on automatically generated and personalized recommendations have primarily focused on exploring the effects in traditional online marketplaces, such as the trust in and adoption of such systems (e.g., Benbasat and Wang, 2005; Hess et al., 2009), the influence on customer’s choice (e.g., Senecal and Nantel, 2004; Benlian et al., 2012; Adam and Pecorelli, 2018), or satisfaction (e.g., Holzwarth et al., 2006; Jiang et al., 2010). Yet, besides one exception (Hodge et al., 2018), research lacks investigations of recommendations in connection with the non-traditional context of robo-advisory (Jung et al., 2018).

3.2.2 Anchoring-and-Adjustment Effect

A recommendation by a robo-advisor can include a piece of information that a user can use as an anchor for further decision-making. The anchoring-and-adjustment effect, or often simply called anchoring effect, is the disproportionate influence on decision-makers to make judgments that are biased toward an initially presented information (Epley and Gilovich, 2006). Heuristics reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations (Tversky and Kahneman, 1974). Accordingly, decisions are made using the given anchor regardless of whether the anchor is relevant and useful for the decision (Furnham and Boo, 2011). Kahneman and Tversky (1974) provide one classical example to demonstrate the anchoring effect. They interviewed their study participants on the fraction of African nations in the United Nations. Based on a generated random number they asked in a first round whether the right answer is higher or lower than the random number. Afterwards, the participant should give a concrete answer to the question. The results showed that the answers of the participants were numbers close to the anchor they were given in the first round.

This experiment shows that the anchor is used as a starting point for a decision, which is adjusted until it matches the anchor (Janiszewski and Uy, 2008). After nearly 40 years' worth of research on the effect, the anchoring effect can be considered one of the most robust psychological processes that influences human decision-making (Furnham and Boo, 2011). The anchoring effect is usually interpreted as a sign of human irrationality, but recently studies suggested that the anchoring effect results from people's rational use of their finite time and limited cognitive resources (Lieder et al., 2018).

The effect has been demonstrated in various domains such as real estate valuation (by experts and amateurs) (Northcraft and Neale, 1987), purchasing of consumer products (Wansink et al., 1998), or savings (Cronqvist and Thaler, 2004). Especially in the area of financial decision-making, anchors seem to play an important role because humans typically do not (want to) spend much time on decision-making in this area (Benartzi and Thaler, 2007). One large impediment to the anchoring effects in savings is liquidity constraints of each customer: Extreme anchor values can have no effect if customers do not have the liquidity to save such or similar volumes (Loibl et al., 2016). Vice-versa, Braeuer et al. (2017) indicated that small anchors in robo-advisory have little or no effect on customers who aim to invest large volumes.

3.2.3 Anthropomorphism, Avatars and Social Presence

A current trend in designing IS and specifically robo-advisory (Hodge et al., 2018) comprises the employment of anthropomorphic cues. Anthropomorphism describes the attribution of humanlike characteristics, behavior, and emotions to nonhuman agents (Epley et al., 2007). It can be understood as a human heuristic to alleviate the understanding of unknown agents by applying anthropocentric knowledge (Griffin and Tversky, 1992; Epley, 2004). Accordingly, Pfeuffer et al. (2019) define anthropomorphic IS as "IS in which the technical and informational artefacts possess cues that tend to lead humans to attribute human-like physical or non-physical features, behavior, emotions, characteristics and attributes to the IS." Thus, the thoughtful design of anthropomorphic cues can lead to an increased recognition of anthropomorphic features by humans, likeability, ease of use, and efficacy of an IS (Burgoon et al., 2000; Epley et al., 2007).

Because anthropomorphism as an innate tendency that influences the decisions and judgements of humans to a large extent, various research fields have been exploring its capabilities and effects in product design and on human behavior (e.g., Nass et al., 1999; Aggarwal and McGill, 2007; Wang, 2017). Studies drawing on social response theory (Nass and Moon, 2000) provide strong evidence that in various situations, humans tend to apply social rules and heuristics to anthropomorphically designed computers. While mental features such as the ability to chat may increase the perception of intelligence in a non-human technological agent, the main goal of visual features, such as appearance or embodiment, is to improve the social connection by implementing motoric and static human features (Eyssel et al., 2010). As such, static and motoric human-like embodiments through avatars (e.g., Holzwarth et al., 2006) have been observed in previous research as an important factor in influencing trust and forming social bonds with virtual agents (e.g., Goetz et al., 2003; Qiu and Benbasat, 2009; Broadbent et al., 2013).

Since IS research is partly concerned with the amalgamation of existing theory with novel aspects of technology, the effects of such anthropomorphic design-elements on the perception of human-likeness must be made measurable and theoretically explainable. Previous efforts in IS research have employed and tested the construct of social presence as a measure of the perception of human-likeness in an interaction partner (Gefen and Straub, 2003; Qiu and Benbasat, 2009). Social presence theory originally describes the awareness of another human partner within a social interaction (Short et al., 1976). The idea to apply the theory of social presence in the form of a psychometric construct to the context of IS arose from the suggestions that theories from (social) psychology may in principle also be applicable to human-computer interaction (Nass et al., 1994). Indeed, previous research in IS has shown that social presence is well applicable as a means of measurement of the perception of a human touch within various IS contexts (Holzwarth et al., 2006; Qiu and Benbasat, 2009). In fact, it appeared that through the construct of social presence, effects of anthropomorphic cues on likeability, trusting beliefs, perceived enjoyment and other important determinants of systems success could be explained (Gefen and Straub, 2003; Tourangeau et al., 2003; Cyr et al., 2007).

3.3 Research Framework and Hypothesis Development

Based on what has been presented so far, a research model was developed that explicates how a robo-advisory's personalized anchor and anthropomorphism increase investment volume directly or by enhancing social presence. Figure 1 illustrates our conceptual research framework. Subsequently, we present the derivations for each of our hypotheses.

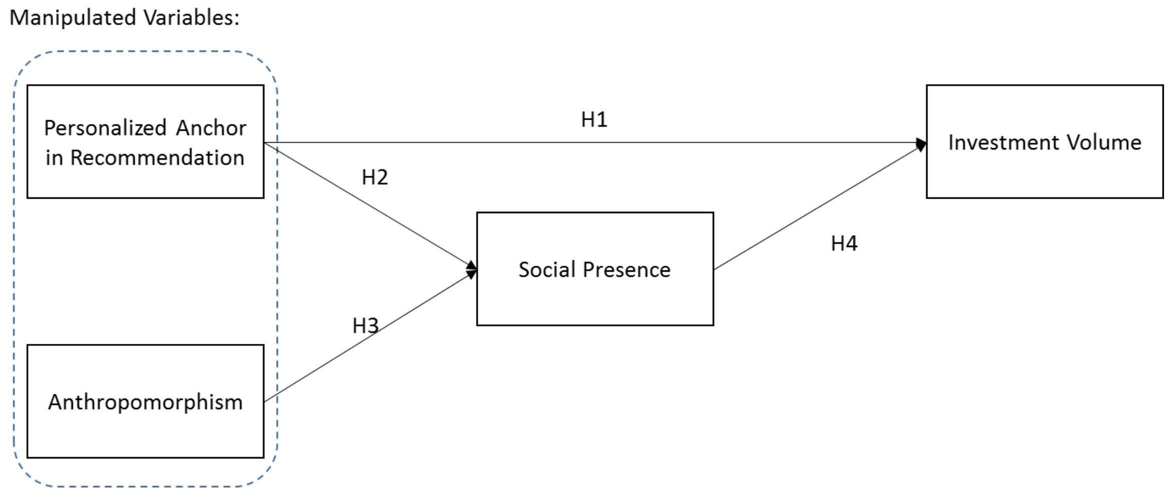

Figure 3-1: Research Framework

3.3.1 The Effect of Personalized Recommendations on Investment Volume

The previous section mentioned that the anchoring effect is a well-known effect that exists in many domains. However, in an investment or savings context, results from studies that manipulate anchors are mixed. Loibl et al. (2016) provided evidence that the same quantitative anchor for all investors had no effect on investors, who were restrained to reach the anchor by their personal liquidity constraints. Simultaneously, low anchors in an investment context revealed to have little or no effect on investors with large investment volumes (Braeuer et al., 2017).

Moreover, there is a shift from traditional offline banking services to online services like robo-advisory which increases the occurrence of decision-making environments in an investment context. Generally, customers tend to underinvest, which may be grounded in the hyperbolic discounting bias (Laibson, 1997). In effect, this bias leads customers to value their present liquidity higher than possible gains in the future, thus discounting their future financial welfare. In the context of robo-advisory, the presence of this bias may influence customers to underinvest, which hinders the possibility of otherwise greater future savings through higher investments for these customers. Addressing this issue within robo-advisory is inevitable, since not only financial service providers may profit from higher investments, but foremost customers may experience greater economic welfare. Based upon the anchoring effect, we aim to demonstrate that an anchor can be placed successfully for all robo-advisory users in such an environment to influence their economic decision-making. The anchor should effectively influence the propensity of customers to invest a higher amount relative to his or her liquidity constraints, thus being personalized and countering under-saving effects. Therefore, we state our first hypothesis:

H1: A personalized anchor in a recommendation increases a user's investment volume.

3.3.2 The Effect of Personalized Recommendations on Social Presence

Recommendations can help in the decision-making process, especially if given by an expert agent (Dalal and Bonaccio, 2010). Through an explicit recommendation for example, the decision of a person can be led into a special direction. Also, a specified recommendation against an option may make the decider to not consider this option anymore. Furthermore, a recommendation without an explicit advice can be made through additional information that was given to one of the options, making certain options more attractive to the decider (Dalal and Bonaccio, 2010). Moreover, recommendations do not only have the function to guide a person in a certain direction but also serve as social support. The existence of a recommendation gives individuals the feeling that they are not alone with making a critical decision, hence creating social presence. This could be achieved through showing compassion and understanding of the feelings associated with the decision (e.g., Horowitz et al., 2001; Dalal and Bonaccio, 2010). Based on these findings, we choose to provide some users with a personalized recommendation, which includes a personalized anchor that is dependent on the user's input. Finally, we derive the following hypothesis regarding the recommendation including personalized anchor:

H2: A personalized anchor in a recommendation increases the social presence of a robo-advisor.

3.3.3 The Effect of Anthropomorphism on Social Presence

A robo-advisor is an IS designed to provide financial advice and can reduce the costs of contemporary human advice services. Therefore, it is important to design a trustworthy, serious, and social atmosphere for the customer when interacting with the robo-advisor (Jung et al., 2017). Anthropomorphic design cues in human-computer interfaces could create this required atmosphere. Holzwarth et al. (2006), for example, showed in several experiments that using an avatar in online shopping positively influences a customer's attitude towards the product as well as purchase intentions. Additionally, the social presence elicited by an anthropomorphic avatar appears to increase customer satisfaction with the retailer (Holzwarth et al., 2006), trust in the presented information on the website, and pleasure to visit and use the website (Etemad-Sajadi, 2016). Qiu and Benbasat (2009) present more specific research findings on decision aiding systems, especially on recommender systems and anthropomorphic design. Their study, for example, revealed that while an anthropomorphic avatar for a recommendation agent had a direct influence on social presence. Thus, we derive the following hypothesis:

H3: Anthropomorphism increases the social presence of a robo-advisory.

3.3.4 The Effect of Social Presence on Investment Volume

As robo-advisory is a relatively new phenomenon (Jung et al., 2018), we use insights from neighbouring domains to derive our next hypotheses. Essentially, financial investment decisions via a robo-advisor base on the relationship between the investor and the advisor who offers financial products. In this respect, the investor-advisor relationship bares similarities to the investor-founder relationship that is developed in the crowdfunding domain (Agrawal et al., 2010). Within the crowdfunding domain, the aspect of social presence has gained some attention (Zhang and Benyoucef, 2016; Raab et al., 2017). Findings from this domain suggest that social presence is of importance to build a strong investor-founder relationship (Lu et al., 2016) and that social presence positively influences the success of a crowdfunded initiative in terms of pledged money. Based on these results from the crowdfunding domain and the results regarding the effects of anthropomorphism and recommendations on social presence as mentioned above, we hypothesize that social presence affects a user’s investment volume.

H4: Social presence of a robo-advisor increases a user’s investment volume.

3.4 Experimental Design

To test our hypotheses, we conducted an online experiment with a 3x2 full factorial design. We simulated an online investment decision with the aid of a robo-advisor, using all six possible combinations of the two independent variables: (1) the degree of anthropomorphism (no, low, or high) and (2) the presence or absence of a personalized anchor in a recommendation.

3.4.1 Manipulation of Anthropomorphism

To examine the influence of anthropomorphism, we designed three robo-advisors with different degrees of anthropomorphism. We used various verbal cues to operationalize the degree of anthropomorphism: Both the low and high anthropomorphism conditions welcomed and took leave of the participants, but only in the high anthropomorphism condition did the robo-advisor introduce itself and used personal pronouns (e.g., “I” and “me”) to signal a personality and identity (Pickard et al., 2014). Additionally, we employed some visual cues that are displayed in Table 1.

Degree of Anthropomorphism	**None**	**Low**	**High**
Picture	-		
Name	-	“Robo-Advisor“	“Robin“
Speech Bubble	No	Yes	Yes

Table 3-1: Operationalization of Anthropomorphism Based on Visual Cues

The first operationalization (i.e., no anthropomorphism) lacked any anthropomorphic design elements. For this treatment, we designed the robo-advisory as very anonymous without any visual or verbal cues (e.g., no picture or speech bubble).

The second operationalization (i.e., low anthropomorphism) employed a few anthropomorphic design elements. The robo-advisor displayed a picture in form of a pictogram and a non-human, function-oriented name (“Robo-Advisor”). Moreover, we designed the interaction as a dialogue between the pictogram and the user by using speech bubbles, signalling rudimentary cues of an actual conversation.

The third and last operationalization used an avatar with a human embodiment adopted from Wünderlich and Paluch (2017) to ascertain tested humanlike appearance cues for the design of the avatar. We, however, gave up other anthropomorphic elements like a voice output or any animations because previous studies have demonstrated that their effects depend on the context and the expectations the user has with regard to the services placed on the website (e.g., McBreen and Jack, 2001; Powers et al., 2003). Moreover, the robo-advisor used first-person singular pronouns as well as displayed a gender-neutral name (i.e., “Robin”) (e.g., Nass et al., 1997; Hodge et al., 2018) and introduced itself to the customer at the beginning of the robo-advisory interaction.

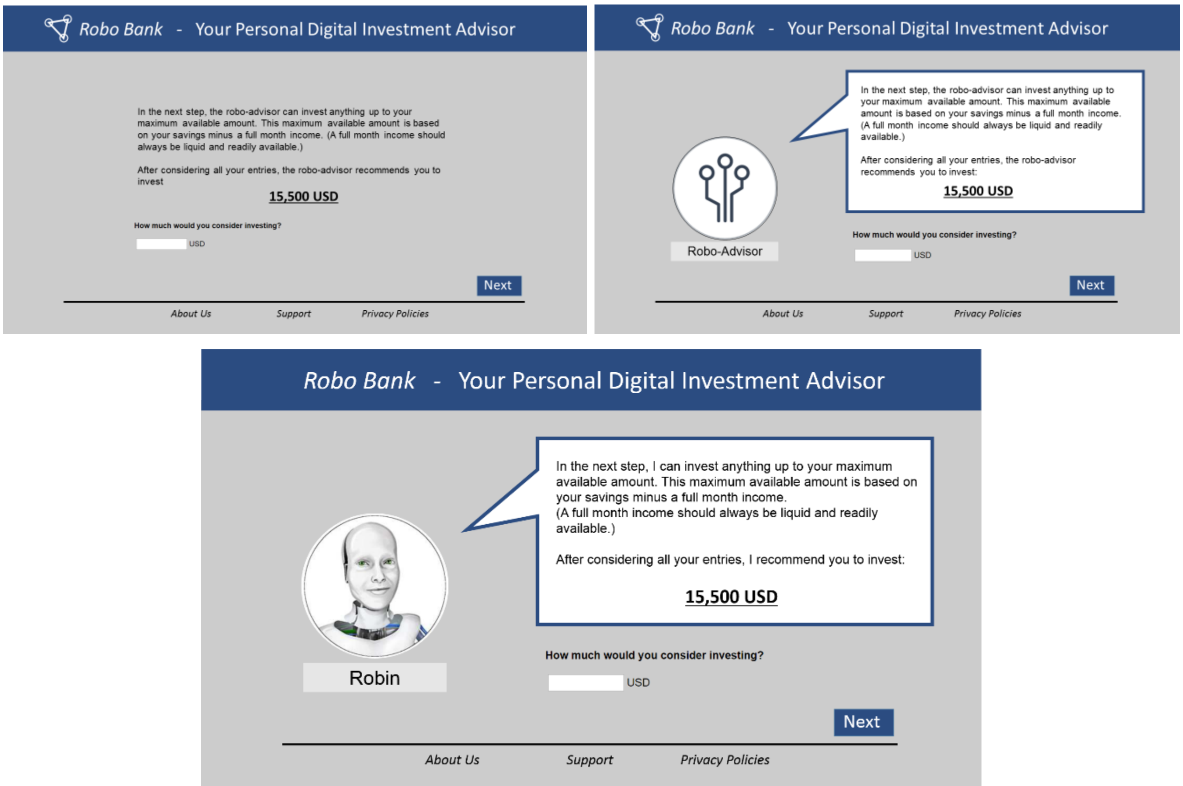

Figure 3-2: Screenshot of the Recommendation Page

3.4.2 Manipulation of Personalized Anchors in Recommendation

To operationalize and calculate a suitable and realistic personalized anchor we designed a recommendation based on contemporary robo-advisors in practice as references.

In the first step, our system calculates the personal maximum possible investment volume of the participant. The personal maximum available investment volume is based on a user's entries with regard to current savings and income per month. Based on contemporary practices, we argued that a full month income should always be liquid and readily available for unexpected emergencies (Havlat, 2018). In contrast, many participants may prefer a higher liquidity instead of investing their savings. Yet, insisting on a higher liquidity than necessary is suboptimal, since the participant may lose out on the possibility of increased economic welfare. Consequently, the personal maximum possible investment volume is calculated per participant as following:

$$Personal\ Maximum\ Investment\ Volume = Savings - 1 * Full\ Month\ Income.$$

Subsequently, our system calculates the personalized anchor in real time. We used 90 percent of the personal maximum investment volume as our anchor value:

$$Personalized\ Anchor = \text{Personal Maximum } Investment\ Volume * 0.9.$$

The personalized anchor was rounded off to hundreds to avoid concurrent adjustment effects due to the different precision of different anchors, as more precise anchors lead to less adjustment (Janiszewski and Uy, 2008). Personalized anchors were combined with an investment recommendation (i.e., "The robo-advisor recommends you to invest…" or "I recommend you to invest…”). The control group did not receive a recommendation and, thus, no personalized anchor. All groups subsequently made an entry about the volume they would invest.

3.4.3 Dependent Variables, Control Variables and Checks

We focus on Social Presence and Investment Volume as dependent variables. The items to measure the dependent variable Social Presence were adapted from Gefen and Straub (2003) (e.g., “There is a sense of human warmth in the website”). They were presented on a 7-point Likert-type scale ranging from strongly disagree to strongly agree. We measured the second dependent variable Investment Volume by the numerical answer the user provided for the question: “How much would you consider investing?”. Users entered absolute values (e.g., 500€) which were then normalized for each user by its personal maximum investment volume for analysis of results later on.

In addition, we also tested various demographics (i.e., Age, Gender, and Previous Experience with Robo-Advisory) and control variables that have been identified as the most influential drivers in extant literature: The items for Personal Innovativeness were adapted from Agarwal and Prasad (1998) (e.g., “I like to experiment with new information technologies”), Trusting Disposition (e.g., “I generally trust other people”) and Product Knowledge (e.g., “How much do you know about robo-advisory services?”) from Qiu and Benbasat (2010), Institution-Based Trust from Hess et al. (2009) (e.g., “I am comfortable making decisions using decision-making software”), Plan for Money Long-Term from Netemeyer et al. (2018) (e.g., “I set financial goals for the next 1-2 years for what I want to achieve with my money”), Product Involvement from Zaichkowsky (1985) (e.g., “I am interested in robo-advisory services like the one provided by Robo Bank”) and Willingness to Take Investment Risks from Netemeyer et al. (2018) (e.g., “When thinking of your financial investments, how likely are you to take risks?”). Additionally, we asked some multiple-choice questions to test the Financial Literacy of the participants (Netemeyer et al., 2018) (e.g., “When an investor spreads his money among different assets, I believe that the risk of losing a lot of money will: increase/decrease/stay the same/don't know”). As manipulation checks, the participants stated whether there was an assistant who helped in making an investment decision and whether the robo-advisor recommended a possible investment volume.

3.4.4 Experimental Procedure

We segmented the experiment in six steps, in which all participants received the same questions (Figure 4): (1) The first part started with a random assignment of the participants as well as with a short introduction of the experiment’s rule set, followed by (2) a simple explanation of the use and functions of contemporary robo-advisors. (3) Participants received the information that they would be interested in investing money and that they would consider investing it in a robo-advisor. Afterwards, participants saw the ad of the fictional company ‘Robo Bank’, and received the instructions to start the advisory service. (4) Comparable to the traditional human advisory process (Jung et al., 2018), the next step represented the configuration phase, where the information asymmetry between the user and the robo-advisor was reduced: Here, similar to contemporary robo-advisors, the robo-advisor introduced itself and asked the user some questions about his or her demographics as well as financial situation and preferences. (5) Subsequently, in the matching & customization phase, the user chose the investment volume. In the personalized recommendation conditions, the robo-advisor would place a personalized anchor in form of a recommendation about the investment volume based on the user’s former entries. In the other conditions, the robo-advisor would just ask the user for the desired investment volume without any indication how much he or she should invest. (6) The final part of the experiment was a survey about the participants’ advisory experience over multiple pages, ending in a short debriefing.

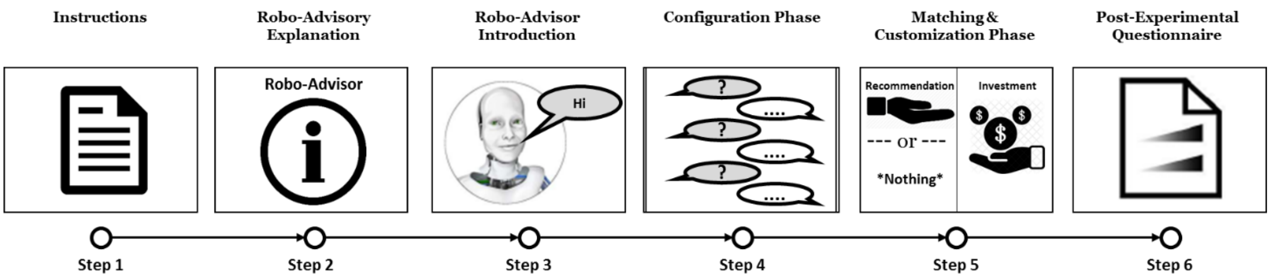

Figure 3-3: Experimental Procedure

3.5 Analysis and Results

3.5.1 Sample Description, Controls and Manipulation Checks

We recruited a total of 557 participants through the crowdsourcing marketplace Amazon Mechanical Turk, a suitable platform to get in touch with Internet-savvy users, who are potential users of robo-advisors. Moreover, we restricted participation to users who are U.S. residents with at least 95 percent approval rate (Goodman and Paolacci, 2017). 145 participants were excluded due to failing manipulation checks as they did not recognize the presence of an avatar and/or a recommendation. Out of the remaining 412, we further screened for participants to ensure eligibility of our participants for robo-advisory services and ascertain the validity of our data: We excluded those who (1) intended to invest more than their actual savings, (2) declared an unusual high monthly income of more than $5,000, and/or (3) were not eligible for robo-advisory services as they declared to have higher monthly costs than income. After all these checks, the final data set consisted of 278 participants.

Groups	N	Female	Average Age (SD)	Previous Experience with Robo-Advisory: yes
1: no recommendation & no anthropomorphism	40	52%	37 (13)	8%
2: recommendation & no anthropomorphism	51	53%	39 (12)	12%
3: no recommendation & low anthropomorphism	36	44%	37 (13)	6%
4: recommendation & low anthropomorphism	45	56%	36 (10)	16%
5: no recommendation & high anthropomorphism	55	56%	39 (13)	5%
6: recommendation & high anthropomorphism	51	53%	41 (15)	16%

Table 3-2: Descriptive Statistics of the Sample

We conducted several one-way analyses of variance (ANOVAs) to confirm the random assignment to the different experimental conditions and to check our control variables. There were no significant differences in demographics in terms of Gender ($F=0.281$, $p>0.1$), Age ($F=0.799$, $p>0.1$) or Previous Experience with Robo-Advisory ($F=1.121$, $p>0.1$) between the six experimental groups and no significant differences regarding Personal Innovativeness, Trusting Disposition, Product Knowledge, Institution-based Trust, Plan for Money Long-Term, Product Involvement, Financial Literacy or Willingness to Take Investment Risks (all $p>0.1$), indicating that these (control) variables did not confound our dependent variables.

3.5.2 Reliability and Validity

Table 3 shows that both, the construct's Cronbach's alpha (0.956) and composite reliability 0.955), were above the recommended level of 0.70 and show a high internal consistency (Nunnally and Bernstein, 1994). We measured Investment Volume directly via the numerical answer of the users and, thus, the construct has the highest reliability. We tested convergent validity based on the values of the loadings and the average variance extracted (AVE). The results show that the loadings of all items were higher than 0.70. AVE was 0.811 and above the recommended level of 0.50, suggesting that on average, the construct explains more than half of the variance of its indicators (Hair et al., 2014). These results confirm the convergent validity of the measures.

Construct	Number of items	Loadings range	Composite reliability	Cronbach's alpha	AVE
Social Presence	5	0.866-0.940	0.955	0.956	0.811

Table 3-3: Reliability and Convergent Validity of Our Principal Construct

We used the heterotrait-monotrait ratio of correlations (HTMT) for assessing discriminant validity as there is evidence of its superior performance to Fornell-Larcker test (Henseler et al., 2015). The maximum value of HTMT was 0.397, below the maximum value of 0.9 suggested by Teo et al. (2008), indicating that the constructs differ from each other and discriminant validity is supported. We also tested for multicollinearity by calculating the maximum variance inflation factor (VIF) which was equal to 1.013. Mason and Perreault (1991) indicate that a VIF of 10 or higher is an evidence for multicollinearity, which is not the case in our data, indicating the absence of multicollinearity.

3.5.3 Hypotheses Testing

We used a partial least squares approach, with the SmartPLS 3 software as widely accepted tool (Mero, 2018). PLS suits this research as the primary focus is on the path relationships and variance explained of the constructs rather than on the model fit per se (Sarstedt et al., 2014)[2]. A path-weighting scheme was used to estimate the path coefficients. A two-tailed bootstrapping with 5,000 subsamples determined the significance levels, reliability, and validity. The model fit determined by SRMR (Henseler et al., 2016) was 0.066, below the cut-off value of 0.08 indicating a good model fit (Hu and Bentler, 1999). Figure 4 indicates path coefficients and significance levels.

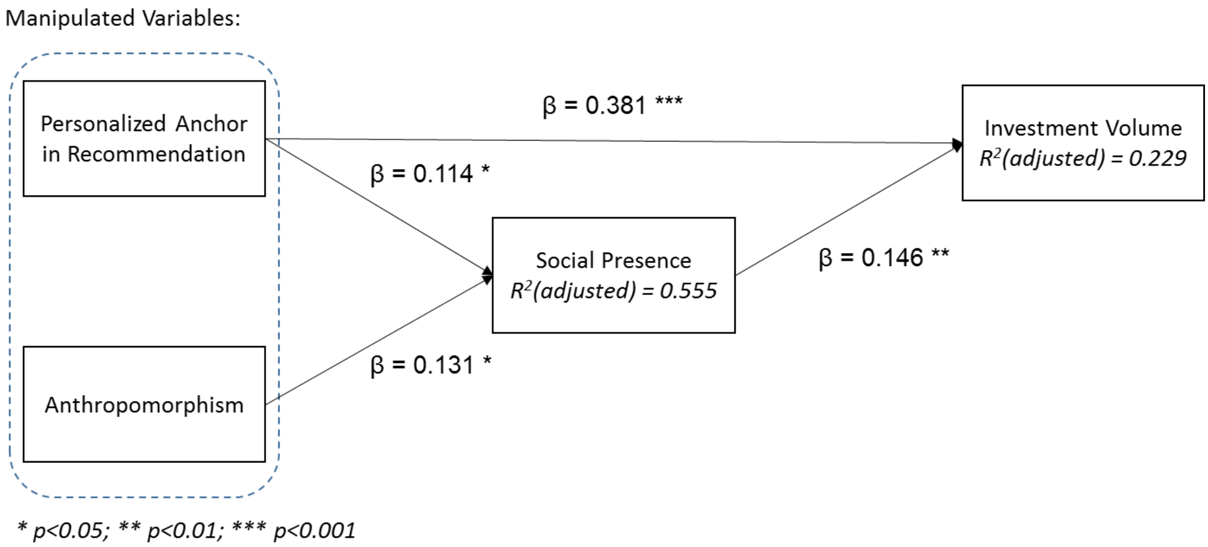

Figure 3-4: Research Model Including Path Coefficients Results

Overall, the results support our theoretical model and hypotheses. The personalized anchor in a recommendation had a positive direct effect on Investment Volume (relative to personal maximum investment volume) with $\beta=0.381$ and $p<0.001$, thus supporting H1 and meaning that the presence of a personalized anchor in a recommendation increased the investment volume independently of the personal maximum investment volume available. The recommendations including personalized anchors had also an effect on Social Presence ($\beta=0.114$ with $p<0.05$) which supports H2. Moreover, as expected, a higher degree of

[2] Additional ANOVAs and planned contrast analyses were conducted that support the results of the PLS analysis.

anthropomorphism led to a higher degree of Social Presence (β=0.131, p<0.05), supporting our hypothesis H3. Increasing Social Presence further resulted in a higher Investment Volume (relative to personal maximum investment volume), supporting H4 with β=0.146 and p<0.01. The anchoring effect was also clearly demonstrated in Figure 5 showing the average investment volumes (relative to the personal maximum investment volume) across the different groups. On the horizontal axis, the figure displays the six different experiment groups (see also Table 2). On the vertical axis, the average investment volume selected by the participants is shown. All groups with a personalized anchor in a recommendation are hatched. For the different conditions of anthropomorphism, the figure illustrates that once the robo-advisor placed a personalized anchor in a recommendation, the average investment volume nearly doubled.

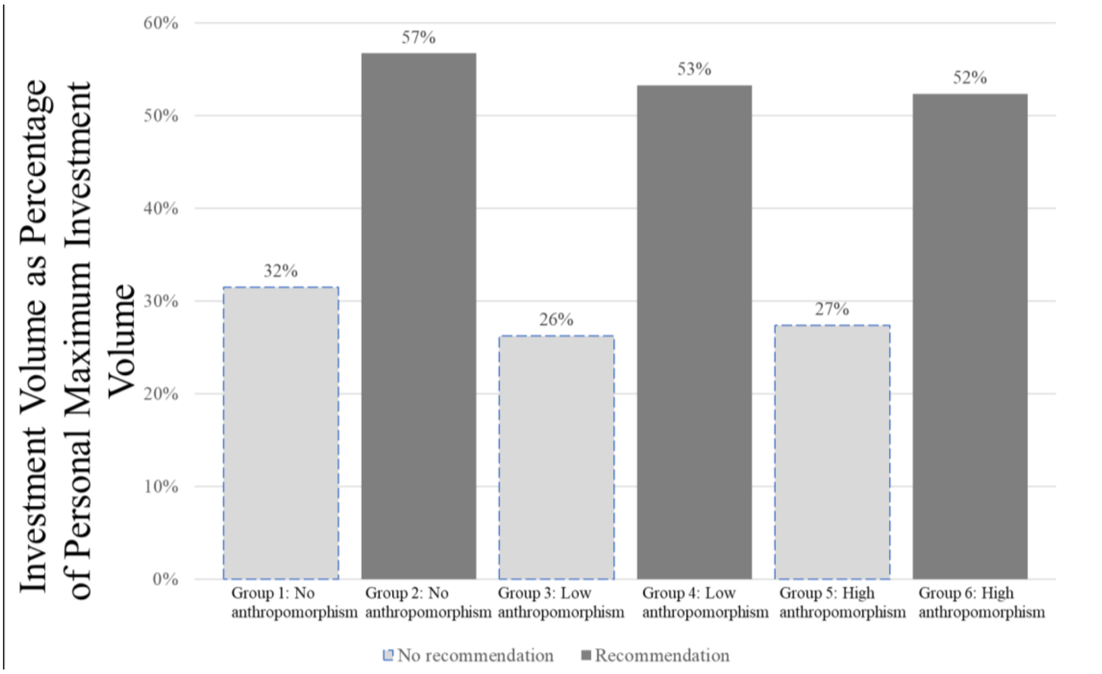

Figure 3-5: Average Investment as Percentage of the Personal Maximum Investment

3.6 Discussion

The effective design of interfaces between users and IS has become an increasingly relevant topic for both researchers and practitioners, as the ongoing technological advancements force companies to rethink contemporary services. This piece of research aimed to show possibilities of effectively designing financial support systems - such as robo-advisors - to increase not only user acceptance and investment volume, but also the propensity to invest. Thus, robo-advisors may help in countering systematic under-savings that reduces economic welfare. Precisely, we examined the effects of advisors with varying degree of anthropomorphism in combination with a personalized anchor placed in a recommendation, whereby the anchor was calculated based on information the user provided.

The most important finding of our study demonstrates that an increasing degree of anthropomorphism in robo-advisors leads to higher perceptions of social presence, which in turn leads to higher investment volumes as well as higher usage intentions. Moreover, our research reveals that personalized anchors in recommendations not only positively influence the perception of social presence, but also have a direct positive effect on investment volumes.

3.6.1 Implications for Research and Practice

Our paper contributes to research by providing a novel perspective on the nascent area of designing financial support systems, but has unprecedented impetus for financial service providers as well.

Following the call to further explore nudging, especially personalization in recommender systems (e.g., Goes, 2013; Weinmann et al., 2016), and to explore the novel robo-advisory phenomenon (Jung et al., 2018), we address the theoretically and practically neglected effects of anthropomorphism and personalized anchors in recommendations as effective nudges in the robo-advisory context (Jung et al., 2018). First and foremost, we provide first empirical evidence that a personalized anchor in a recommendation carried out by a robo-advisor directly increases the investment volume of users. Furthermore, we demonstrate how anthropomorphic design cues in conjunction with personalized recommendations can additionally increase the investment volumes through the mediation effect of social presence. Most importantly, we depart from prior research by examining how these anthropomorphic design elements impact economic decision-making. These findings may provide a foundation for further research in the directions of robo-advisory, service personalization or impact of human-like IS on economic behavior.

From a managerial point of view, our research has relevant implications for financial service providers as well. Building a familiar, socially-oriented atmosphere through anthropomorphic design elements in form of verbal and visual cues as well as the pronunciation of a personalized anchor may be simple mechanisms for robo-advisors because it can increase the investment the user would make. We showed how robo-advisory can profit from IS by calculating personalized anchors in real-time. These anchors served as cues that effectively mitigate possible underinvestment and therefore influenced users to make more future-oriented economic decisions. Thus, we not only shed theoretical light on our investigated manipulations and derived learnings for providers of financial services to increase investment volumes, but also discovered IS design elements with a possible impact on the future welfare of today’s society.

3.6.2 Limitations, Directions for Future Research and Conclusion

Despite the aforementioned contributions of this research, the conducted studies should be treated as an initial examination into the research field of financial support systems. Therefore, we want to point out some noteworthy limitations and directions for future research.

First, our experiment was designed as an online survey, so that the results do not represent actual robo-advisory with a binding investment decision. It would be interesting to test our hypotheses in a field study with a real robo-advisor to further explore external validity. Second, we also examined only social presence as a potential mediator. Here, further mediators and moderators which are also relevant in the research of the effect of computational agents like trusting beliefs and perceived enjoyment could be examined. Also, other dependent variables, such as user satisfaction or financial well-being, could be explored. Third, further research could investigate the degree of anthropomorphism that is accepted by the customer. In our experiment, for example, the chosen avatar was a gender-neutral static picture with a humanlike looking but without any motions. Some possible research directions would be the influence of an animated avatar, the effect of a voice output, or the influence of an avatar with a clear gender. However, the designers should be careful: The use of anthropomorphism must be coordinated with the context and the number of anthropomorphic elements should be well-thought-out (Seymour et al., 2018). In case that the anthropomorphic design of the system deviates from the expectations of the users, it may create a feeling of eeriness and may lead to a decrease of trust in the system (i.e., “uncanny valley”) (Mori, 1970).

Overall, our study is an initial step towards better understanding how the design of interfaces may improve economic decision-making in the context of financial support systems. Specifically, we shed light on the effects of anthropomorphism and personalized anchors in recommendations in the design of robo-advisors. We hope that our study provides impetus for future research on digital nudges as well as actionable recommendations for designing IS.

Chapter 4: Recommendations in Augmented Commerce

Title: Recommendations in Augmented Reality Applications - the Effect of Customer Reviews and Seller Recommendations on Purchase Intention and Product Selection (2018)

Authors: Martin Adam, Technische Universität Darmstadt, Germany

Mario Pecorelli, Technische Universität Darmstadt, Germany

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Abstract

Not only since the launch of Pokémon Go in July 2016, augmented reality (AR) has received a big boost in awareness and popularity. AR-based start-ups have entered the market, and established companies start to offer AR functionalities in their smartphone applications. A new distribution channel in form of augmented commerce has been emerging, although only little is known about optimized design of AR environments due to the limited number of user studies re-searching the effects of AR usage. This paper's research objective is to tackle this gap by analysing AR technology in combination with online recommendations, a well-established, ubiquitous design element in today's e-commerce. We conducted a controlled online experiment with 208 subjects to examine the effects of customer recommendations (CR) and increasingly emerging seller recommendations (SR) in AR applications. Our results demonstrate that CRs in AR ap-plications positively influence the intention to purchase and the selection of products by de-creasing a customer's product fit uncertainty, whereas SRs displayed no significant influence. These insights are the first steps to further understand how AR and online recommendations can be used and have to be implemented to provide customers with novel and accepted sources of value.

Keywords: Augmented Reality, Recommender Systems, Digital Nudging, Product Uncertainty

4.1 Introduction

Augmented reality (AR) is a direct or indirect view of a physical, real-world environment that allows to add virtual, computer-generated elements that 'augment' the perception of the user. Since the invention of the first prototype 'The Sword of Damocles' built in the 1960s (Sutherland, 1968), technology has advanced tremendously. With 2.3 billion smartphones (Statista, 2017) and 1.23 billion tablet users (Statista, 2017) worldwide, the possibility of using AR is available for more people than ever before. Under these circumstances, AR is on the verge to become the next defining technology in the mobile channel. Hence, AR commerce is on the rise and according to estimates, AR and virtual reality has the potential to generate $150 billion in revenue by 2020 (Gaudiosi, 2015)

Despite the steady growth of AR commerce and the economic forecasts, AR has received only little attention from IS researchers yet. Recently, Harborth (2017) showed that AR user studies are underrepresented in the IS domain. So far, the majority of AR research is about the development and presentation of new AR technologies. Hence, as of today, little is known about how AR environments can be enhanced through informational design features. The need for more corresponding AR research was already exclaimed over 10 years ago by Swan II and Gabbard (2005, p. 1-2) and still persists today: "What these approaches do not tell us, and what, to date has not been researched, is how information should be presented to users," and "for AR devices to reach their full potential, what is now required are new paradigms which support heads-up information presentation and interaction".

Digital nudges refer to the use of user-interface elements to improve the outcome of the decision making process of individuals online and are one of the most important technologies in today's e-commerce. There is manifold IS research that has investigated digital nudges in various contexts, such as user assessment of website value (Benlian, 2015), scarcity and personalization cues in seed stage referrals (Koch and Benlian, 2015), the impact of free sampling strategies in freemium conversion rates (Koch and Benlian, 2017), and how software updates influence user attitude (Fleischmann et al., 2016). In fact, the most widespread digital nudges are online recommender systems (ORS), which are algorithms that use historical, demographic or heuristic data to make recommendation vicarious for the seller (Xiao and Benbasat, 2007). Previous research about ORSs has primarily focused on exploring the effects in traditional online marketplaces, such as the trust in and adoption of such systems (Wang and Benbasat, 2005), the influence on consumer's choice (Senecal and Nantel, 2004) or satisfaction (Jiang et al., 2010), but lack investigations in connection with non-traditional technologies like AR. However, AR-enabled technologies might be able to revolutionise the use of ORSs. The obligatory AR peripherals, like cameras and sensors combined with analysation algorithms and techniques lead to easy data collection of users and their surroundings. The usage of AR commerce applications, automatically provides more precise, current and relevant information for sellers than all other used forms of e-commerce, utterly effortless for both sides of the transaction. Hence, this can enhance the ORS endorsements, letting them surpass today's value by making them more personalised, suitable and fitting. Thereby, SRs in conjunction with AR possibly have a greater influence on customers' perceived product fit uncertainty than without AR, leading to a mediation effect on product selection that might be greater than similar effects of CRs. Consequently, if CRs are less valuable or even completely obsolete in AR commerce applications, sellers can go without them, avoid their disadvantages entirely and use ORSs instead to regain complete control over the product recommendations process, without any drawbacks. To investigate the possible divergent effects of SRs and CRs in AR commerce, research crucially needs to examine them in AR environments.

The paper sheds light on the effect of seller and customer recommendations in AR on customer's product fit uncertainty, based on data collected in an online experiment with 206 participants. The objective is to extend the manifold online product recommendation research by adding AR as a new context and observe the effects separately for SRs and CRs. Moreover, we seek to examine the influence of SRs and CRs on product selection in AR commerce applications by investigating the related user's product fit uncertainty and its mediating effect. Lastly, this work gives practical implications for practitioners on how online recommendations should be used as of today to improve the effectiveness in AR commerce applications.

This paper is divided into three parts. First, we present our theoretical foundations on AR, online recommendation and product fit uncertainty as well as our hypotheses. Second, we provide a detailed description of the conducted online experiment. Third, we elaborate on the results of the study, discuss the findings and give an outlook for future research.

4.2 Theoretical Foundation and Hypothesis Development

4.2.1 Augmented Reality

Milgram and Kishino (1994) describe AR as a mixed reality, a subset of virtual reality technology that merges the real and the virtual world. AR displays an otherwise real environment with added virtual objects to enhance the view of the user. While AR is often connected to the use of head-mounted displays, most definitions agree that AR is not restricted to a particular technology.

Today's AR applications are manifold, whereby the biggest ones are commerce, education and entertainment (Carmigniani and Furht, 2011). Commercial AR applications aim to simplify the user's life. For example, IKEA provides an AR application that allows users to see how new furniture looks in their homes and check whether it fits without measuring or moving in the actual environment. Education applications are mostly about cultural or sightseeing experiences. For instance, a museum can give additional information through AR about their exhibits or can offer interactive tours. Entertainment applications include pure AR-based presentations, such as AR games or more traditional applications with AR features. The biggest broad market AR phenomenon so far was the launch of Pokémon Go in 2016, a cross-platform mobile device game with AR features. In 2017, the game still has 65 million monthly users and has generated about 1 billion in revenue since it was released (Forbes, 2017).

Early research by Swan II and Gabbard (2005) reviewing AR technology-related papers found that although the majority of the extant work focussed on human perception and cognition on low-level tasks in AR and the impact of AR technology on user task performance: Only two papers focussed on design decisions and user interaction in AR environments (Azuma and Furmanski (2003); Lehikoinen and Suomela (2002). Recent research from Harborth (2017) examined in a systematic literature review the current state of AR studies in the IS domain and highlighted that most AR-related IS research focusses on either reviewing or developing new AR technologies. He confirmed that user studies represent a minority accounting only 21.92% of all AR related papers in the IS domain. Most of these studies focus on the effects and benefits of AR on different domains, such as education or status quo technologies (e.g. Djamasbi et al., 2014; Krishna et al., 2015; Phil et al., 2015). Others are about the acceptance, potential and adaption of AR by firms and the broad market (e.g. Gautier et al., 2016; Kumar et al., 2016; Ross and Harrison, 2016). The two papers that are closest to the topic of AR environment designs are by Huang and Liu (2014), investigating the importance of a narrative storyline in AR applications, and by Nguyen et al. (2012), observing the effectiveness and advantages of mobile devices as smart shopping assistant in retail stores.

However, none of these studies dealt with concrete design decisions of AR environments and their corresponding effects on the user, leading to a considerable research gap. As a result, informational design features like online recommender systems in AR commerce applications are practically used by many online marketplace websites, but are understudied in the context of AR research. Especially emerging AR-enabled techniques, such as simultaneous localization and mapping (Reitmayr et al., 2010), make it easy to collect and process information about the user and their surroundings by analysing the customer provided live picture.

4.2.2 Online Recommendations

According to estimates, an amount of 10% to 30% of online retailers' sales are coming directly from recommendations (Mulpuru et al., 2007). Previous studies indicated that subjects, who consulted product recommendations, selected the recommended products twice as often as subjects who did not (Senecal and Nantel, 2004). Online recommendations are predominantly impersonal information sources as they usually consist of online word-of-mouth (OWM) (e.g., user reviews and ratings), on the one hand, and of ORSs, on the other hand.

OWM uses data provided by former customers to generate subjective experience-driven recommendations. Other peoples' opinions can be considered even more valuable than private information (Banerjee, 1992; Banerjee, 1993) and, eventually, influence the user's decision-making (McFadden and Train, 1996). However, CRs have their disadvantages and need certain circumstances to be effective. Since, the conformity effect is one of the reasons CRs work (Lascu and Zinkhan, 1999; Lee et al., 2008) there is an idle time before a critical number of votes or reviews is reached. Additionally, like bad reviews, a large number of too good reviews can also have a negative effect (Maslowska et al., 2016). Further, the ideal product for the majority of people, may not be the right choice for every individual customer. Moreover, CRs, as an additional source of information, reduce the seller's influence over the customer. If AR applications are able to give personalised and fitting product recommendations, CRs are possibly obsolete in AR commerce, leaving the influence over the customer to the seller. Therefore, the individual contribution of SRs and CRs need to be separately examined in AR contexts.

In comparison to CRs, recommendations made by sellers in online marketplaces are usually made by ORSs, using algorithms that work like "a salesperson who is highly knowledgeable about both the alternatives and the consumer's tastes" (Ariely et al., 2004, pp. 81-82). These systems use variations of historical data (e.g., search and purchase history) and current data (e.g., consumer behavior) to generate recommendations. Although recommendations can have great influence on product choice (Xiao and Benbasat, 2007) and are usually more influential than other sources (Senecal and Nantel, 2004), online transactions are typically between people or firms that have little information about each other. This makes them vulnerable to opportunistic behavior (Ba and Pavlou, 2002). The competitive customer-seller-relationship (Evans and Beltramini, 1987) causes customers to assume that the sellers act mainly for their own good, making recommendations by their systems less trustworthy.

Despite the negative perception of SRs, ORSs are an important feature for the shopping experience in online markets because "a wealth of information creates a poverty of attention"

(Simon, 1971, p.40). Although online marketplaces lower the search costs for product information and quality information (Stiglitz, 1989), the myriad of easily presentable product alternatives rises the search costs to identify the ideal product (Chen et al., 2004). The huge amount of possible alternatives creates heavy cognitive loads for customers, making it more difficult to choose (Chen et al., 2004). ORSs help customers to process the overwhelming amounts of information and alternatives by presenting a small selection of only relevant, fitting options to them (Häubl and Trifts, 2000; Senecal and Nantel, 2004). They reduce search costs and improve the quality of customer decisions, resulting in increased customer satisfaction (Hanani et al., 2003; Komiak and Benbasat, 2006; Xiao and Benbasat, 2007). In fact, customers who interacted with ORSs reported a more positive shopping experience than customers who did not (Felfernig and Gula, 2006).

4.2.3 Product Fit Uncertainty

Uncertainty is defined as a situation in which not all information is available, clearly defined or reliable (Merriam-Webster Dictionary, 2017). The uncertainty in online market places is distinguishable into seller uncertainty, the incapability of predicating the seller's behavior that arises from the information asymmetry, and product uncertainty, the lack of information that prevents a buyer to assess all characteristics of a product (Pavlou et al., 2007). Following Hong and Pavlou (2010) product uncertainty can be split into three distinct dimensions: description uncertainty (i.e., inability to identify product characteristics), performance uncertainty (i.e., uncertainty about product's future performance), and fit uncertainty (i.e., doubt if product's characteristics and buyer's needs match), with only product fit uncertainty yielding a significant effect on price premiums, satisfaction, product returns, and repurchase intentions.

The effectiveness of a recommendation depends on the type of product (Bearden and Etzel, 1982; Childers and Rao, 1992; King and Balasubramanian, 1994). In general, two categories of products exist: search goods and experience goods. In contrary to search goods, whose characteristics are easily observable before the purchase, the value of experience goods can only be truly determined by consuming or experiencing them (Nelson, 1970; Collier, 2012). Since it is impossible to completely evaluate their attributes, a purchase involves an amount of risk that has a direct negative effect on transaction behavior (Jarvenpaa et al., 2000; Featherman and Pavlou, 2003). Pre-purchase information scarcity refers to the effect that customers can't evaluate all quality attributes before the purchase (Wells et al., 2011). Unlike consumers in retail who can examine products with their hands and eyes to assess the product's physical information, the disadvantageous circumstances of e-commerce lead to an even bigger information asymmetry which amplifies uncertainty (Chen et al., 2004; Wells et al., 2011).

4.2.4 Hypotheses and Research Framework

Although online marketplaces lower the search costs for product and quality information (Stiglitz, 1989), the myriad of easily presentable product alternatives automatically rises the search costs to identify the ideal product (Chen et al., 2004). The huge amount of possible alternatives creates heavy cognitive loads for customers, making it more difficult to choose (Chen et al., 2004). Studies have shown that ORSs help customers to process and handle the overwhelming amounts of information (Häubl and Trifts, 2000; Senecal and Nantel, 2004). In fact, subjects, who consulted product recommendations, selected the recommended product twice as often as subjects who did not (Senecal and Nantel, 2004).

Therefore, we hypothesise that customers take the evaluations of other customers and of the seller as an informational source that helps them determining whether they want to buy a product and if so, which item they will select (Ardnt, 1967; Olshavsky and Granbois, 1979; Duhan et al., 1997). Specifically, we expect that even in the new environment of AR, recommendations are accepted information cues and, therefore, increase the likelihood of the customer to buy a product.

H1a: *Customers will be more likely to buy a product if the presented products have been recommended by other customers in comparison to the situation without any CR.*

H1b: *Customers will be more likely to select a product that has been recommended by other customers in comparison to a product without any CR.*

H2a: *Customers will be more likely to buy a product if the presented products have been recommended by the seller in comparison to the situation without any SR.*

H2b: *Customers will be more likely to select a product that has been recommended by the seller in comparison to a product without any SR.*

Since uncertainties are caused by incomplete information availability, recommendations are able to compensate the drawbacks that arise from product uncertainty partially. In the current state, particularly OWM has proven to be more influential for experience goods than ORSs (Dellarocas, 2003; Godes and Mayzlin, 2004). By knowing other consumers' experiences, the uncertainty and perceived risk of buying is lowered (Lee et al., 2008) due to the conformity effect, influencing the customer's decision making and quality (Chen et al., 2004; Senecal and Nantel, 2004; Xiao and Benbasat, 2007).

Therefore, we hypothesise that recommendations are not only informational cues to indicate demand or reduce effort, but also sources to decrease the uncertainty related to product fit. The recommendation by other customers signals that the product has been bought and, thus, tested before and that the perceived likelihood that the product will work and fit in general is increased.

With regards to SR, easy and detailed personal data collection through AR has two theoretical effects: First, when using the information extracted from customer's video stream it automatically provides an explanation on how and with which data the seller's system derives its recommendations, strengthening the users' trusting beliefs in the competence and benevolence of the system and resulting in an increased users' trust and satisfaction (Wang and Benbasat, 2004). Second, sellers can mitigate the customer's product fit uncertainty by giving highly personalised recommendations, derived from the characteristics of the customer's direct surroundings that fit in size, colour, and style. Thus, we expect that CRs and SRs, individually, will reduce product fit uncertainty and, thus, partly mediate the main effect on intention to purchase and selection of the offered products.

H3a: *Product fit uncertainty will mediate the effect of CR on customer's intention to purchase.*
H3b: *Product fit uncertainty will mediate the effect of CR on product selection.*
H4a: *Product fit uncertainty will mediate the effect of SR on customer's intention to purchase.*
H4b: *Product fit uncertainty will mediate the effect of SR on product selection.*

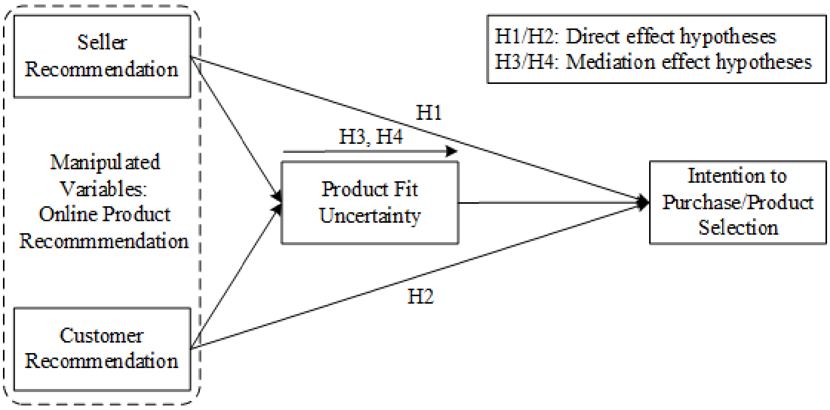


Figure 4-1: Research Framework

4.3 Research Methodology

4.3.1 Experimental Design

To test our hypotheses and the effectiveness of recommender systems in AR environments, a 2 (CR: absence vs presence) x 2 (SR: absence vs presence) full factorial design online experiments on computers was conducted. 208 Participants were recruited through Amazon Mechanical Turk (AMT), a business marketplace for on-demand workforce, and received a monetary compensation for their survey participation. Based on the recommendation by Goodman and Paolacci (2017), we only accepted AMT participants with an approval rate higher than 95%. The participants were set in a shopping scenario in which they were instructed to use an AR shopping application to buy furniture. We segmented the experiment into three parts. The first part started with a short introduction of the experiment's rule set and a simple definition and example of AR and AR commerce. In the second part, we told the attendees that they want to buy a new bookshelf for their living room. Afterwards the fictional company 'Augmented Furniture' was introduced through an ad and the participants were told that they decided to use Augmented Furniture's AR shopping application for their purchase. The next page showed a smartphone with a picture of a living room as a starting situation for the AR application. Scenarios with SR got two extra screens with manipulations that underline the SR calculation process. Then, the participants were presented a choice scenario with two different shelves, similar in most features: design, size, prize and colour. The participants then had to choose a shelf. At this point the buying process stopped. The final part of the experiment was a survey about the participants' shopping experience over multiple pages ending in a short debriefing.

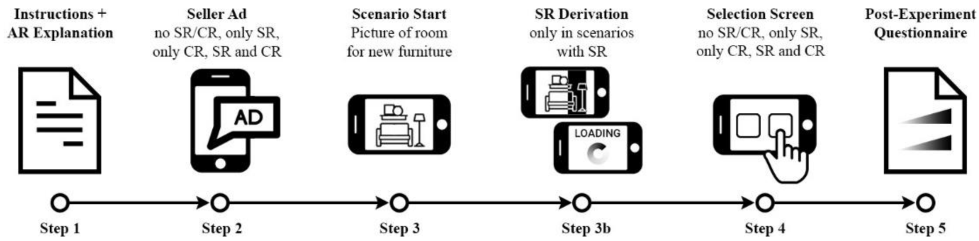


Figure 4-2: Experimental Procedure

1.1 Manipulation of Independent Variables

For the manipulations in the experiment, we used a SR and a CR to represent two different forms of online recommendation. The participants were randomly assigned to one of four groups that included either no recommendation, only a SR, only a star rating as established form of CR, or SR in conjunction with star rating. Figure 3 shows the ad of the fictional firm 'Augmented Furniture', including an extra text description for every type of recommendation used in a scenario, as a short introduction.

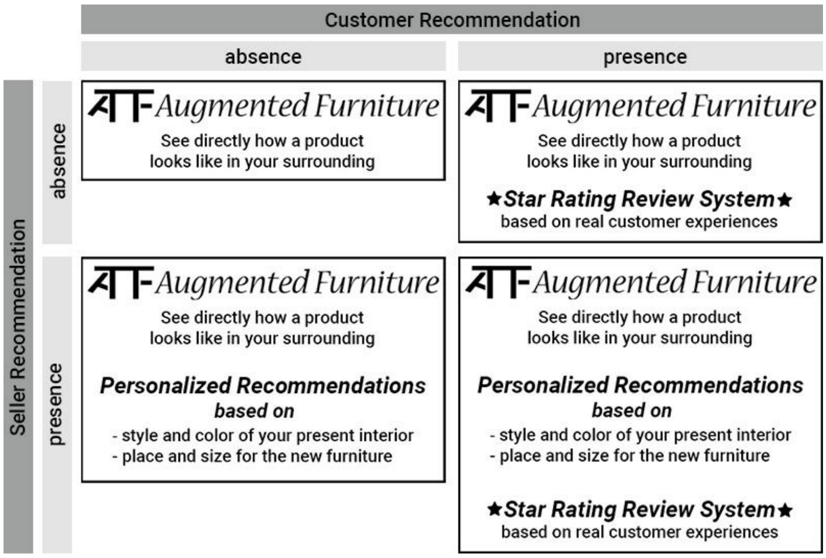


Figure 4-3: Ad Configuration for Different Scenarios

In the scenarios with the SR, participants received two extra screens prior to the selection screen to indicate and simulate that a personalised recommendation is calculated with a waiting time based on the individual properties of the room pictured in the live video feed (Moon, 1999). First, they saw an animation of the application scanning the whole room. Afterwards they were presented a loading animation, with a text 'Please wait. We are looking for a product that is best for you', in which the recommender system took the scanned properties into account and calculated the individual best fit product. After a certain while the calculations finished and the animation changed, displaying the recommended item with a text above saying 'We have a recommendation for you'.

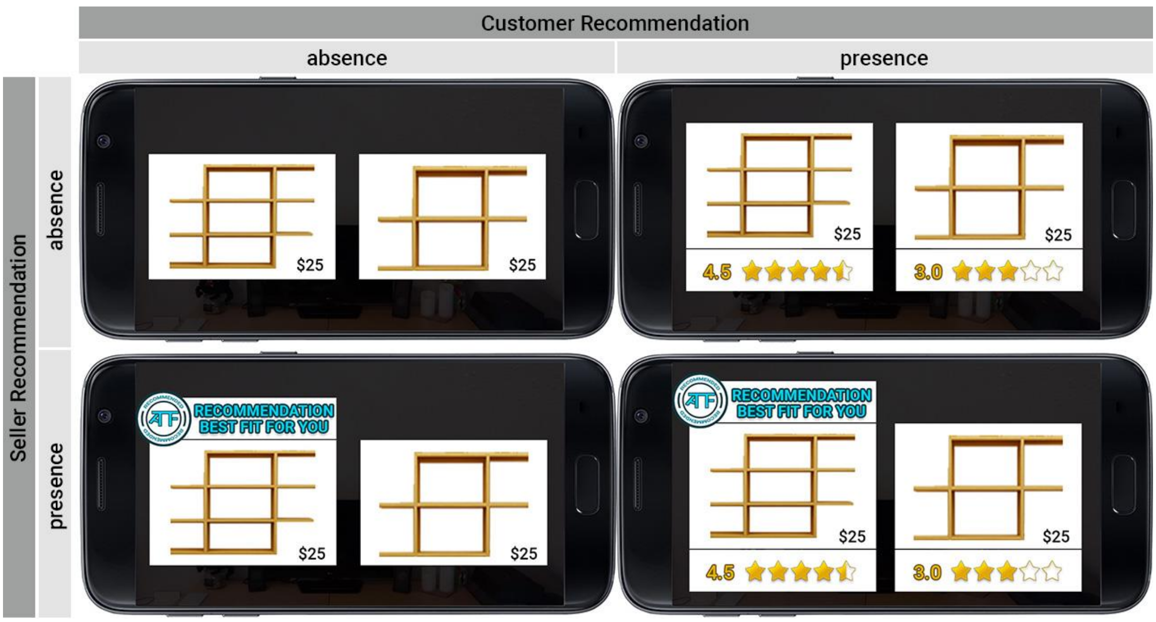


Figure 4-4: Selection Screen for Different Scenarios

The selection screen of all scenarios displayed the same two products. However, the left product, as the recommended option, was highlighted correspondingly to the used types of recommendation in each scenario. For SR, a text along with a logo that emphasized the connection between the recommendation and the firm ‘Augmented Furniture’ was added above the product. Further, Maslowska et al. (2016) found out that sales were higher for products with ratings between 4.2-4.5 stars and decreased for even higher ratings of 4.5-5.0 stars. To avoid cross-effects for the CR, the recommended left shelf got a rating inside the optimal rating range of 4.5 stars and the right shelf got a rating of 3 stars to be less preferable but still a valid alternative. SR and CR were positioned in their ‘usual positions’ where customer expect them to be, based on the practice of today’s top e-commerce websites (e.g. Amazon and Walmart). Star ratings are usually placed below, while seller recommendation (e.g. ‘Bestseller’) are usually placed above the product picture on the selection screen.

4.3.2 Dependent Variables, Control Variables and Manipulation Checks

The dependent variables are the intention to buy any of the presented shelves as well as the proportion of the chosen shelves in the different conditions. While the intention to buy serves as an approximation for the likelihood to purchase in real life, the proportion of the chosen shelves indicates any shift in preferences between the available products. Whereas the intention to purchase was measured by an adapted single item (Meyers-Levy and Peracchio, 1996) on a 7-point Likert-type scale, we measured the proportion of shelves by a binary variable, which equals 0 when a participant selected the left (recommended) shelf and 1 when the right shelf was selected, divided by the total number of participants in the respective subgroups. The predictive validity of single items is comparable to multi-item measures (Bergkvist and Rossiter, 2007; Sarstedt and Wilczynski, 2009). Moreover, in addition to our mediator variable product fit uncertainty, we also tested for age, gender and various control variables that have been identified as the most influential drivers in extant literature: The items for product fit uncertainty (PFU) were adapted from Hong and Pavlou (2010), seller uncertainty (SU) and product quality uncertainty (PQU) from Dimoka et al. (2012), product involvement (PI) from Zaichkowsky (1985), familiarity with product class with regards to previous knowledge (PK) and usage experience (PE) with shelves and augmented reality applications from Johnson and Russo (1984). Moreover, we used several items from the scale about risk propensity (RP) from Meertens and Lion (2008) and need for conformity (NFC) from Bearden and Rose (1990). All aforementioned items were measured on a 7-Point Likert-type scale with anchors majorly ranging from strongly disagree (1) to strongly agree (7). All scales exhibited satisfying levels of reliability ($\alpha > .7$). A confirmatory factor analysis also showed that all analysed scales exhibited satisfying convergent validity. Furthermore, the results revealed that all discriminant validity requirements (Fornell and Larcker, 1981) were met, since each scale’s average variance extracted exceeded multiple squared correlations. Since the scales demonstrated sufficient internal consistency, we used the averages of all latent variables to form composite scores for subsequent statistical analysis. Online shopping experience and internet usage were measured based on respondents' statements in years and hours per week, respectively. Lastly, one attention and two manipulation check questions were included in the experiment. We used the checks to ascertain that participants comprehended and followed the instructions and that our manipulations were successful and noticeable. Moreover, we used one item to measure perceived popularity of the left shelf (Van Herpen et al., 2009) to check the manipulation of our CR directly. Additionally, we assessed participants' perceived degree of realism and overall comprehension of the instructions and presented information with two items on a 7-point Likert-type scale.

4.4 Analysis and Results

4.4.1 Sample Description, Controls and Manipulation Checks

208 participants were included in the final dataset. 291 respondents filled out the survey without missing a question or failing our attention check. Out of these 291, 83 were removed because they failed our manipulation checks and could not properly recall either whether and how many stars the presented products had or whether the application explicitly recommended a shelf. The average age of the respondents was 37 years, ranging from 18 to 72. Table 1 summarizes the descriptive statistics of the data.

	Mean	SD
Demographics		
Age	36.93	11.55
Gender (Females)	56%	
Controls and Mediator		
Seller Uncertainty (SU)	3.09	1.03
Perceived Quality Uncertainty (PQU)	3.48	1.17
Product Involvement (PI)	4.23	1.70
Risk Propensity (RP)	5.09	1.06
Need for Conformity (NFC)	4.00	1.21
Online Time (hours/week)	28.50	18.38
Online Shopping Experience (years)	10.89	4.95
Product Knowledge: Shelves (PK_S)	4.34	1.61
Product Experience: Shelves (PE_E)	4.90	1.64
Product Knowledge: AR (PK_AR)	3.09	1.80
Product Experience: AR (PE_AR)	2.64	1.66
Product Fit Uncertainty (PFU)	3.91	1.54

	Mean	SD
Dependent Variable		
Intention to Purchase		
SR absent _ CR absent	3.76	1.73
SR present _ CR absent	4.33	1.86
SR absent _ CR present	4.44	1.72
SR present _ CR present	4.93	1.65
Selection (Left Shelf)		
SR absent _ CR absent	59%	
SR present _ CR absent	67%	
SR absent _ CR present	89%	
SR present _ CR present	89%	

Table 4-1: Descriptive Statistics

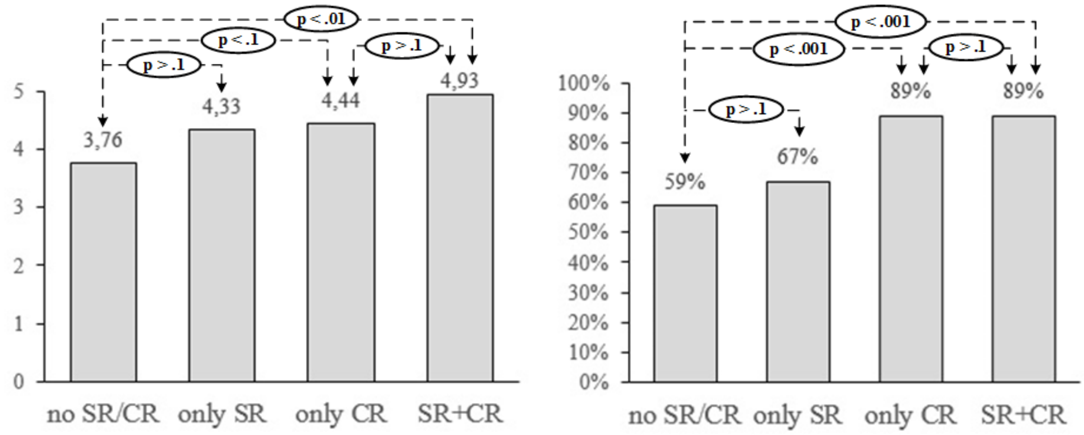


Figure 4-5: Results for Intention to Purchase (left) and Product Selection of Shelf A (right)

We conducted several one-way ANOVAs to determine whether the random assignment of participants to the different experimental outcomes was successful. The results confirm the success since no significant difference (p>.1) was found between the experimental groups. Consequently, respondents' demographics and controls were homogenously present across our four conditions and do not confound the effects of our manipulations. Moreover, we checked whether our manipulation by CR also impacted perceived popularity. Results demonstrate that perceived popularity of the left shelf was significantly higher among the two groups with the CR than in the two without (F=61, df=1, p<.001). To check for external validity, we assessed the participants' answers regarding their perceived degree of realism of the experiment. Degree of realism reached high levels ($\bar{x}$ = 4.99, σ=1.52), thus we can assume that the manipulations worked as intended and the experiment was considered realistic.

4.4.2 Main Effect Analysis

To test the main effect hypotheses, we first performed a three stage hierarchical linear regression on the dependent variable intention to purchase (see Table 2), following other researchers (e.g., Hayes, 2017, p. 71) who consider OLS regression an acceptable analysis for examining our dependent variable. We first entered all controls (Block 1), then added the manipulations SR and CR (Block 2) and lastly inserted the mediator product fit uncertainty (Block 3). Although CR (p<.05) demonstrated a statistically significant direct effect for intention to purchase, SR surprisingly did not (p>.05). After adding our mediator, product fit uncertainty showed a statistically significant effect (p<.001), while CR was still significant, indicating partial mediation. Therefore, our findings show that participants confronted with a CR have significantly higher intentions to purchase than those who are not confronted with CR, regardless whether the application presented a SR or not. This indicates that presenting customers CRs in augmented reality applications increases the likelihood of them to purchase a product.

	Block 1		Block 2		Block 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	.326	0.949	.105	0.978	3.175**	0.978
Manipulation						
SR			0.334	0.182	0.224	0.166
CR			0.524**	0.184	0.355*	0.170
Mediator and Controls						
PFU					-.465***	.074
SU	.073	.138	.089	.135	.028	.123
PQU	-.250	.132	-.275*	.129	-.096	.121
Gender	.453	.213	.380	.209	.296	.192
Age	.004	.009	.001	.009	-.001	.008
PI	.606***	.062	.585***	.061	.399***	.063
RP	-.083	.094	-.071	.092	-.046	.086
NFC	.230**	.078	.245**	.077	.146*	.072
OTime	-.006	.005	-.007	.005	-.005	.005
OShopping	.003	.021	.010	.020	.023	.019
PK_S	-.012	.098	-.005	.096	.011	.087
PE_S	.026	.090	.040	.088	.053	.081
PK_AR	.030	.102	.060	.100	.106	.091
PE_AR	-.033	.108	-.070	.106	-.081	.097
Adjusted R^2	0.448		0.473		0.561	

Note: * $p<.05$; ** $p<.01$; *** $p<.001$, N = 208.

Table 4-2: OLS Linear Regression on Intention to Purchase

Moreover, we also investigated the effect of SR and CR on the proportion of the chosen shelves. Therefore, we performed a three stage hierarchical binary logistic regression on the dependent variable selection (Table 3). Just as before, we first entered all controls (Block 1), then added the manipulations SR and CR (Block 2) and lastly inserted the mediator product fit uncertainty (Block 3). Again, we inspected Nagelkerke's R^2 and computed χ^2-Statistics to examine the model's significance for all stages. Similar to the effect on intention to purchase, our SR did not display a significant effect on the selection of the products but CR did (b=-1.740, Wald statistic (1) = 12.745, $p<.001$). If customers see a CR that clearly favours a product, they are more than five times as likely to choose the recommended product (coded as 0) in contrast to the other presented product (coded as 1). When we added the mediator, perceived fit uncertainty exhibited a significant influence on selection as well ($p<.001$) while CR was still significant, indicating partial mediation. Thus, the higher the perceived fit uncertainty of the left shelf, the less likely people will choose that product.

	Block 1			**Block 2**			**Block 3**		
Intercept	Coefficient	SE	Exp(B)	Coefficient	SE	Exp(B)	Coefficient	SE	Exp(B)
Constant	3.171	1.860	23.841	3.867*	1.969	47.816	-5.297	2.902	.005
Manipulation									
SR				-.008	.384	.992	.404	.460	1.498
CR				-1.693***	.416	.184	-1.740***	.487	.176
Mediator and Controls									
PFU							1.263***	.254	3.536
SU	-.395	.265	.674	-.469	.283	.625	-.137	.321	.872
PQU	.108	.252	1.114	.153	.268	1.166	-.270	.317	.764
Gender	-.131	.415	.878	-.161	.458	.851	.248	.533	1.281
Age	-.015	.019	.986	-.012	.021	.988	-.010	.025	.990
PI	-.447***	.121	.640	-.440***	.127	.644	.023	.170	1.023
RP	-.255	.183	.775	-.166	.198	.847	.029	.238	1.029
NFC	-.180	.151	.835	-.274	.165	.760	.013	.214	1.013
OTime	-.019	.011	.981	-.019	.011	.982	-.029*	.014	.971
OShopping	.056	.039	1.057	.046	.042	1.047	.045	.052	1.046
PK_S	.126	.205	1.135	.174	.218	1.190	.289	.262	1.335
PE_S	-.022	.188	.978	-.079	.201	.924	-.273	.235	.761
PK_AR	.349	.196	1.417	.384	.213	1.468	.270	.255	1.310
PE_AR	-.262	.208	.770	-.266	.221	.766	-.148	.272	.862
-2 (Log Likelihood)	193.823			174.701			135.419		
Nagelkerke's R^2	0.209			0.324			0.528		
Omnibus Model $\chi 2$	30.902**			50.024***			89.305***		

*Note: * p<.05; ** p<.01; *** p<.001, N = 208.*

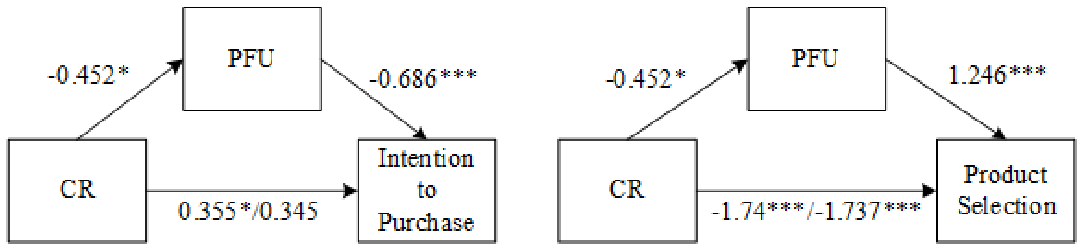
Table 4-3: Binary Logistic Regression on Product Selection

4.4.3 Mediation Effect Analysis

For our mediation hypotheses we argued that the CR would affect the intention to purchase as well as the selection of the bookshelf through the perceived product fit uncertainty. Thus, we hypothesized that in the presence of a CR the product uncertainty decreases and, hence, the intention to purchase increases and selection of the recommended product is more likely. Therefore, in a mediation model using bootstrapping with 1,000 sampled and 95% bias-corrected confidence interval, we analysed the indirect effect of our CR on intention to purchase and selection through product fit uncertainty. We conducted the mediation test applying the bootstrap mediation technique (Hayes, 2017).

To analyse the process driving the effect of our CR on intention to purchase (product selection), we inserted product fit uncertainty as our potential mediator between CR and intention to purchase (product selection). For our dependent variable intention to purchase, the indirect effect of CR was statistically significant, thus perceived fit uncertainty mediated the relationship between CR and intention to purchase: indirect effect = 0.31, standard error = 0.135, 95% bias-corrected confidence interval (CI) = [0.072, 0.621]. Moreover, CR was negatively related with product fit uncertainty ($b= -0.452$, $p<.05$), and higher perceived product fit uncertainty was associated with lower level of intentions to purchase ($b=-0.686$, $p<.001$; see Figure 6), whereas the direct effect of our CR became insignificant ($b=0.345$, $p>.05$) after adding our mediator product fit uncertainty to the model.

Therefore, our results demonstrate that product fit uncertainty significantly mediated the impact of CR on intention to purchase: Our CR reduced the product fit uncertainty and, thus, increased the intention to purchase. Similar results could be found when inserting product selection as our dependent variable: indirect effect=-0.564, standard error = 0.334, 95% bias-corrected confidence interval (CI) = [-1.116, -0.002]. However, product fit uncertainty only partially mediated the effect of CR on selection (Figure 6). The reason for this mismatch is that other aspects that may also influence product selection were not considered. For example, the bandwagon effect (Van Herpen et al., 2009) states that if people have to select a product they tend to follow the crowd but it does not increase the intention to purchase the product. We conducted the same mediation analyses with SR as our independent variable on intention to purchase and product selection as dependent variables, yet no significant direct or indirect effect could be observed.



Note: Coefficients were computed based on mediation analysis using bootstrapping with 1,000 samples and a 95% bias-corrected confidence interval (Hayes, 2017); we included both manipulations and all control variables in the analysis; the first coefficient on a given path presents the direct effect without the mediator in the model. The second coefficient presents the direct effect when the mediator is inserted in the model. * p<.05, ** p<.01, *** p<.001.

Figure 4-6: Mediation Analysis

4.5 Discussion, Implications and Future Research

In the past, IS AR research has majorly focused on topics regarding the development of new AR technologies and has neglected user behavior. This imbalance implies the risk that users are omitted while technology advances. The objective of our paper was to shed light on some of the effects on users of the relatively new, but steadily growing broad market AR technology. Therefore, two forms of online recommendations, seller and customer recommendation, were tested in an AR commerce environment. Our results strongly support our hypotheses that customers can be nudged in their product selection and purchase behavior by online recommendations. However, not all online recommendations are significantly influential as demonstrated. Our findings show that CR is an influential information source, whereas SR is not. Moreover, the effect of CR was mediated by product fit uncertainty, reflecting the influence of other customers' recommendations on the parts of perceived risk associated with buying the product. However, no effect was found for the SR manipulation.

This paper contributes to AR IS literature by merging the research on a rising technology that is on the verge to sustainably change the way customers shop with human-centered investigations of the effects of SRs and CRs on users in the early stages of AR commerce. The study's main theoretical implication relates to the impact of online recommendations on customer's online purchase intention and product selection. The results extend existing online product recommendation research by showing that the effects of SRs and CRs in AR environments are similar to the effect in traditional online market places. As the Internet emerged and online commerce started to bloom, customers have gained access to new sources of information that can provide non-personalised recommendations, such as customer reviews in form of star ratings, as well as personalised recommendations, such as seller recommendations. Even though past results showed that personalised recommendations influence more than non-personalised ones (Brown and Reingen, 1987; Senecal and Nantel, 2004), that is not true for seller recommendations. Particularly, the collected data does not reflect the expected theoretical advantages that an AR-based commerce system may have for customers and sellers with personalised recommendations that are directly derived from real-world data. Consequently, AR's full potential it not usable at the moment, so in relation to SRs AR commerce cannot exceed the other more established e-commerce platforms, yet. Although, the existing algorithms in AR can create individualized value for customers, there are two possible reasons preventing SRs from having a significant impact on the intention to purchase or product selection. First, especially in e-commerce scenarios in which all contact points are impersonal, the competitive customer-seller-relationship (Evans and Beltramini, 1987) creates suspicion that prevents customers from trusting the recommendation. Second, emerging technologies usually miss user acceptance (Davis, 1989) and therefore fail to utilise their full potential. Thus, users underestimate the true value and usefulness of the AR SR in the beginning. The results could change in the next few years if AR is used more frequent and becomes accessible for a broader market. More and more people will get familiar with AR technology, and user acceptance may rise. Consequently, our study contributes to AR IS literature and consumer research by analysing the influences of emerging recommender systems and influences on customer decision processes as AR and technology in general advance.

Our paper carries practical implications for marketers as well. First, we demonstrated that CRs are also influential and worthwhile in AR applications. Precisely, customers were more than five times as likely to choose a customer recommended product. The tested star rating is by far the most established form of online-word of mouth and is, therefore, known by almost every customer that has ever bought something online. The outcomes of our study extend the manifold research and applications by validating its effectiveness in a new technological environment. Second, the results showed that CRs decreased the perceived uncertainty of users and thereby mediated the impact of the manipulation. For practitioners this leads to the conclusion that star ratings are accepted and work as intended in AR environments and can directly be used as usual in AR commerce applications. However, these observations were only significant when taking customers as a source of information. When the seller functioned as the source and provided a recommendation with regards to personalised product fit, no significant effect was found. Even though an AR application enables advanced technologies that might be able to give individual and highly fitted recommendations, as for our experiment these endorsements had no effect on the outcome at all. Consequently, practitioners who want to use automatically generated recommendation in AR commerce at that moment have to address the acceptance and trust of the customer, for example, potentially by communicating the advantages more strongly and explaining how exactly the system derives the recommendations. The value for the customer seems to exist but is not yet accepted.

Moreover, since research on AR, online product recommendations and product uncertainty has just begun, our study provides several more avenues to explore. This paper is a basis for future research focusing on the phenomenon of SRs in AR environments and finding determining reasons for their ineffectiveness. Since the study was conducted in an experimental setting with a simplified version of an AR application and with people from the crowdsourcing platform AMT, future research needs to confirm and refine the results in a more realistic setting, such as a field study with a real AR application and gear. Further, a longitudinal design approach can be used to measure the influence when people get more and more used to AR over time. Furthermore, other established and emerging recommendations need to be examined in AR. With our study we investigated the effects on product fit uncertainty and controlled for seller uncertainty and product quality uncertainty, but other forms of effects of ORSs, such as perceived enjoyment, perceived decision quality, perceived product diagnosticity and perceived decision effort (Xu et al., 2014), need to be researched as new technologies and, thus, new forms of value creation will evolve. Lastly, our study does not experimentally and statistically explain why SR was not significant in contrast to CR. Comprehending the current state of the acceptance of the AR technology as well as the SR is a worthwhile endeavour for future research to help AR technology and SRs keep developing and finding more acceptance regarding use and value creation for customers.

Chapter 5: Sold-Out Products in Reward-Based Crowdfunding

Title: The impact of sold-out early birds on option selection in reward-based crowdfunding (2019)

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Abstract

To incentivize early contributions in reward-based crowdfunding, project creators frequently offer reward options in limited numbers, of which the "early bird" is one of the most prominent. Early birds offer the same rewards as an alternative option, but are reduced in price. Although studies suggest that scarcity can influence backers' decisions, research lacks knowledge of whether early bird options impact backers' decision-making once these options are sold out but still visible to potential contributors. Drawing on the phantom effect theory, this multi-method study investigates (1) how phantom alternatives impact backers' selections of available options, and (2) how the phantom effect interacts with different levels of discount and social proof. Our results from an online experiment with 512 participants and a longitudinal observational study based on 676 crowdfunding projects reveal that phantom options make backers choose the equivalent but undiscounted reward option more often. This effect is stronger with a moderate amount of discount for the early bird option rather than a high one. Moreover, social proof (i.e., number of backers who have chosen the early bird option) interacts with the discount amount in that higher levels of social proof weaken the relationship between the amount of discount and the phantom effect. These results show that, contrary to the traditional offline retail perspective, where sold-outs usually hurt sales, sold-out early birds may help in increasing funding revenues in reward-based crowdfunding, if employed strategically. Thus, we provide counterintuitive learnings for research as well as fundraisers looking for capital through reward-based crowdfunding.

Keywords: Early Bird Offers, Stock-Outs, Phantom Effect, Social Proof, Reward-Based Crowdfunding

5.1 Introduction

Internet-based crowdfunding platforms have become successful stages to raise investments for entrepreneurial ventures and innovative products through various small contributions. With a total funding volume of more than $34 billion worldwide in 2015, crowdfunding can be considered one of the most successful contemporary funding models (Mollick, 2014; Massolution, 2015) and already accounts for more funding than venture capital (Barnett, 2015). Of the various kinds of crowdfunding platforms, reward-based crowdfunding platforms (e.g., Kickstarter and Indiegogo) have attracted the most attention from the general public. Contrary to traditional financial investment activities, contributors on these platforms (also known as backers or pledgers) do not obtain a financial return for their funding. Instead, they usually receive a non-monetary reward, such as a book or software (Simons et al., 2017). As these rewards are considered a key incentive for contributors to invest in projects (Kuppuswamy and Bayus, 2013), the contents and the presentation of the reward options play a crucial role in receiving more pledges and higher average pledge amounts. Though reward-based crowdfunding has received considerable attention from scholars (e.g., Wessel et al., 2016; Yuan et al., 2016; Xiao and Yue, 2018), only few studies have provided precious learnings about how reward options influence backers' option selection and thus campaign success (Tietz et al., 2016; Simons et al., 2017; Weinmann et al., 2017). Our comprehension of the effect of the design of reward options menus is thus still incomplete and more research is required to fully understand how to nudge (i.e., guide) backers towards more desirable rewards.

A remarkable, yet hitherto ignored influence in the design of reward option menus is the phantom effect. This effect refers to the impact of sold-out reward options which, though sold out, can still influence backers' reward selection decisions. Reward-based crowdfunding platforms usually allow project creators to offer reward options in limited numbers or for a limited time. One of the most common and widely practiced form of these limited rewards is the "early bird", in which a reward option is offered a second time with the same reward content, but at a reduced price and limited in quantity. Kickstarter (2018) promotes this practice to "build momentum during the project's early days." Consequently, one can assume that early birds have a positive impact on the project success, which also explains their abundant employment in practice. However, limited research attention has been devoted to the effects of those early birds once they are sold out (Yang et al., 2017; Adam et al., 2018). In fact, sellers in offline retail contexts (e.g., brick-and-mortar stores) and common e-commerce environments (e.g., Amazon) usually link unavailable options to undesirable results (e.g., Campo et al., 2003; Sloot et al., 2005; Anderson et al., 2006) and thus attempt to avoid or hide these stock-outs. In reward-based crowdfunding, however, sold-out options typically remain visible including the amount of discount on the sold-out early bird and number of backers who have chosen the early bird, although these early birds have become unavailable for the potential backer. Thus, the question arises if and how these displayed yet unavailable reward options (i.e., phantom options) influence the decision making of potential backers when selecting an available option. As such, our aim is to shed light on the so far neglected impact and the underlying mechanism of the presence and absence of sold-out reward options in reward-based crowdfunding. Moreover, we analyse how the amount of discount impacts this effect, and whether there is an interaction effect between this cue and the number of backers – conceptualized as social proof in our study – who are mentioned to have chosen the early bird. In summary, we aim to answer the following research questions:

RQ1: *How do sold-out early birds influence backers' option selection (phantom effect)?*

RQ2: *How does the discount amount on the sold-out early bird influence backers' option selection?*

RQ3: *How does the number of backers of the sold-out early bird interact with the effect of the discount amount in the sold-out early bird?*

To address these research questions, we use a multi-method approach comprising (1) an online experiment with 512 participants simulating the pledging process of a reward-based crowdfunding campaign and (2) a follow-up observational study based on longitudinal data from 676 *Kickstarter* crowdfunding campaigns that displayed sold-out early birds. Drawing on the phantom effect theory, our results reveal that when a sold-out early bird is present (vs. absent), backers choose an equivalent but undiscounted option more often. This effect is stronger with a moderate (vs. high) discount on the phantom option. Moreover, social proof interacts with the amount of discount in that higher levels of social proof weaken the relationship between the amount of discount and the phantom effect.

This paper provides contributions for researchers, crowdfunding platform operators, and fundraisers. First, following the call by Weinmann et al. (2016) to conduct more research on digital nudging, we address the theoretically and practically neglected effect of sold-out reward options by examining the phantom effect as an effective nudge in reward-based crowdfunding environments and demonstrating how sold-out early birds influence backers' choices. Second, we depart from prior research (Yang et al., 2017; Adam et al., 2018) by investigating how discount amount cues in sold-out reward options counterintuitively affect selection decisions, in that the relationship between discount amount and backers' selection behavior follows an inverted U-shape. This indicates that an exaggerated or low discount in the sold-out reward option leads to a lower likelihood of selecting the same undiscounted reward option in comparison to a moderate discount amount. Third and lastly, we demonstrate that attributes of the phantom options do not exist in a vacuum and are influenced by contextual cues. In particular, we also demonstrate that social proof moderates the curvilinear impact of the discount amount based on the adequacy and consistency of the presented information sources. Thus, we not only shed theoretical light on the phantom effect, but also derive learnings for entrepreneurs and platform operators to increase the total funding amount and thus the probability of success for their crowdfunding campaigns, if they consider and apply our findings strategically.

5.2 Theoretical Background

5.2.1 Rewards in Reward-Based Crowdfunding

The term "crowdsourcing" refers to the concept of outsourcing jobs or tasks to a large, often anonymous group of individuals called the "crowd". Likewise, in contrast to traditional funding mechanisms by which a small group of individuals funds the project with large amounts per person, crowdfunding intends to collect small amounts from a large number of contributors. In this paper, we focus on reward-based crowdfunding, in which backers receive a non-financial reward for their investment. To collect funds, entrepreneurs create a campaign on a crowdfunding platform to pitch their idea or product. The campaign typically includes the project's title, a description, pictures/drafts of the idea or product and a promotional video. Most projects introduce unpublished products and, if potential backers are genuinely interested in a product, they have to pick one of the reward options as the product is usually not offered elsewhere.

As rewards are a key incentive for pledgers to contribute to a campaign (Kuppuswamy and Bayus, 2013), entrepreneurs create a number of project-related rewards and reward options (i.e., reward tiers) to persuade potential backers to support the venture financially. Entrepreneurs can offer a discrete number of project-related reward options which are ascendingly sorted based on price. Kuppuswamy and Bayus (2013) list the following most common reward types on Kickstarter: project-related objects (e.g., a copy of the promoted product), creative integration of the backer into the project (e.g., the appearance as a background actor in a movie), creative experiences (e.g., a day at the recording studio), and creative keepsakes (e.g., photographs from the movie set). Ideally, the designed reward option menu allows the creators to sell the most rewards at the highest obtainable contribution per pledge to reach the highest possible funding for the campaign. Thus, fundraisers not only attempt to persuade potential contributors to back their ventures, but also to nudge the convinced backers towards reward options that provide higher funds for the campaign. Consequently, as reward options play a critical role in reaching the funding goal, examining mechanisms that make backers select more contributory reward options more often is an impactful endeavor.

In information systems (IS) research, only few papers have tackled the topic of the influence of the design of reward option menus on backers' selections: Tietz et al. (2016) showed how decoy options can make backers select an expensive reward option more often, Simons et al. (2017) demonstrated that backers prefer reward options in the middle of a reward option menu, and Weinmann et al. (2017) revealed that scarcity cues in reward options can make these options more attractive and increase funding success. Paradoxically, Joenssen and Müllerleile (2016) analysed projects on Indiegogo with and without scarcity cues and found that scarcity signals have a negative effect on project success. Similarly, Yang et al. (2017) analysed projects from Kickstarter and found that incorporating limited reward options is helpful in attracting new backers, yet having sold-out reward options in the menu resulted in a funding demotivation of subsequent backers. In sum, there are still inconclusive findings regarding whether sold-out reward options actually hurt or help in increasing campaign funding, so that research leaves an unfathomed field for further studies to fully understand the effect of the reward option design. This paper intends to fill this gap by examining how sold-out early birds can influence backers' selections of available reward options.

5.2.2 Early Birds, Stockouts and the Phantom Effect

Reward-based crowdfunding platforms permit fundraisers to offer reward options in limited numbers to signal exclusivity and create interest and excitement among potential backers (Kickstarter, 2018). Whereas some rewards (e.g., hand-crafted work) are naturally limited and cannot be offered in unlimited supply, other rewards (e.g., special editions) are artificially limited. One of the most common forms of artificially limited options is the so-called "early bird" offer, which is limited in quantity or only offered for a limited period. In reward-based crowdfunding, early birds based on limited supply, in which a common reward is offered at a lower price in a limited quantity, are commonly used to accelerate initial demand and create momentum (Kickstarter, 2018). Research has shown that the first received contributions are one of the most critical variables that indicate whether a campaign will reach its funding goal

(Stadler et al., 2015). Thus, early birds are usually associated with increased chances of successful funding. However, only limited research attention has been devoted to how these early birds influence backers' selection of the still available options once sold out (Yang et al., 2017; Adam et al., 2018).

At any point in time, on average 8 percent of all stock keeping units are sold-out in a common retail store (Corsten and Gruen, 2003). Independent of the offline or online context, sellers usually judge these naturally arising stock-out cues (e.g., empty shelves) unfavorable and a challenge to their business. The reason for this attitude is based on findings that customers who encounter stock-out situations either postpone their purchase, turn to a different seller, select an alternative option, or completely abandon their purchase intention (e.g., Campo et al., 2003; Sloot et al., 2005; Anderson et al., 2006). These reactions are majorly associated with negative implications for a company's profitability (Jing and Lewis, 2011), so that sellers attempt to evade stock-outs (Verhoef and Sloot, 2006). The reward-based crowdfunding ecology, however, provides a unique set-up, in which reward options are not removed from the campaign page once they are sold out. Instead, many platforms, such as Kickstarter and Indiegogo, automatically move these no longer available options to a separate section in the reward option menu. Consequently, sold-out early birds are usually still clearly visible to potential backers and thus keep on existing as phantom options that inform contributors of previous selection behavior.

The phantom effect is the influence of the presence of an option that looks real but is unobtainable when the decision is made (Pratkanis and Farquhar, 1992). The concept of the rational individual is based on the premise that dispensable information does not impact individual's decision-making. This theory, however, ignores the fact that individuals choose in numerous environments with unique characteristics, so that contexts can significantly influence individuals' decision-making (e.g., Bettman et al., 1998). As such, in reward-based crowdfunding, although an early bird phantom option is sold out, it can still affect the preferences of the individuals and thus the selection share of the available options in the choice set. Moreover, besides the price and the reward content of the reward option, these phantom options usually still indicate the amount of price discount they have in comparison to their counterpart (i.e., the equivalent but undiscounted reward option) and the number of backers who have chosen the early bird (i.e., social proof). Thus, various discount amounts and social proof cues are not only common and abundant in practice, but at the same time also provide theoretically intriguing influences, which in turn may change the relative meaning and effect of the phantom early birds[3].

5.3 Hypothesis Development and Research Framework

5.3.1 Phantom Effect of Sold-Out Early Birds

Once potential backers visit a campaign, they try to infer information about competing reward options from webpage cues (i.e., features that present a source of information that individuals can use to infer some meaning and that trigger responses). This information may be provided by the product description or the available reward options, but also by phantom reward options. We hypothesize that a phantom option influences the decision-making so that potential backers are more likely to select the reward option equivalent to the phantom option. More precisely, phantom options work as social proof cues that signal information in form of product demand and popularity (Cialdini, 1993; Amblee and Bui, 2012) and can help individuals in inferring product value. Thus, they can communicate the desirability and value of attributes that are existent or non-existent in the remaining reward option menu. For instance, the unavailability of a certain option also reflects the results of previous selection decisions, thus implying the evaluation and judgment of previous backers, assuming that the evaluation and judgment of the previous backers was based on sound reasoning (Naylor et al., 2011). Therefore, potential contributors can socially infer information from the presence of sold-out early birds, which might not be possible with only still available reward options. Moreover, people usually infer that a behavior is right when a lot of people do it and tend to follow that behavior (Van Herpen et al., 2009). Therefore, potential backers use the social proof of the phantom option as an effective indicator to determine the value of the available options (Burnkrant and Cousineau, 1975) and tend to conform with previous selections (e.g., Rao et al., 2001; Goldstein et al., 2008; Van Herpen et al., 2009; Zhang, 2010).

H1: *The presence (vs. absence) of a sold-out early bird increases the selection of the available reward option with the same reward content (phantom effect).*

5.3.2 Phantom Effect, Desirability and Urgency to Buy

We also want to investigate the underlying rationale for the phantom effect. Prior research on scarcity found that options that are low in stock are considered popular and high in value (Van

[3] We consider only early birds that are equivalent to another reward option in the option menu with regard to option content, so that price of the reward option is the only difference between the early bird and the counterpart.

Herpen et al., 2009; Parker and Lehmann, 2011). Phantom options are expected to be perceived similarly. Although the information of the sold-out option is not directly useful to customers, as they cannot select that option anymore, customers may derive indirect information from the rewards in the sold-out early bird about the rewards in the available option, as the value of an option can be deconstructed into the values of the individual features of the option (Lancaster, 1966). Thus, we expect that customers attribute the stock-out to other backers' desirability for and high value assessment of the rewards in the options (Huang and Zhang, 2016). Consequently, those social inferences shift choice preferences towards reward options that share the features that are included in the sold-out early bird.

According to Gupta (2013), a consumer can feel a sense of urgency to buy a product right away. This urge is often created by sellers who employ messages, such as "while supplies last" and "only few items left" (Inman et al., 1997). This effect is usually explained by commodity theory (Brock, 1968), which says that products become more desirable when they are scarce instead of abundant. Sellers use these limited availability messages to create pressure on consumers to buy instantly while the absence of these messages, for example in ongoing offers, leads to no urgency to buy in consumers. Consequently, customers can feel an urge to purchase immediately, as they might not be able to buy the product in the future (Wu et al., 2012) because others will have already done so (Verhallen and Robben, 1994). In stock-out situations in reward-based crowdfunding, the sold-out early bird is not available anymore, but the rewards in it are. Although the other reward options may be unlimited, so that there is no real additional reason to assume that the rewards will become unavailable, we hypothesize that the fact that the early bird has sold out will lead to a higher sense of urgency to buy the equivalent but still available reward option.

Collectively, this research proposes that (1) when backers are exposed to a situation in which they see a sold-out early bird, (2) they perceive the rewards in the sold-out early bird more desirable. Consequently, (3) backers feel a higher urgency to buy the reward option that provides equivalent rewards as the one in the sold-out early bird and thus (4) rather select the similar reward option.

H2: *An increase in the backer's perception that the rewards in the sold-out early bird are more desirable increases the selection of the available reward option with the same reward content via an increase in urgency to buy.*

5.3.3 The Effect of the Discount Amount of a Phantom Option

The effect of a phantom option does not occur in a vacuum but is influenced by the design of the reward option. In retail environments, customers often lack complete information to judge a product or item on its characteristics. Consequently, they try to infer knowledge about the products quality and offer value from available sources and signals, such as price, market offerings, and communication (e.g., Chernev and Carpenter, 2001). Generally, humans pursue the best value for their investments and, therefore, seek to attain monetary advantages. For instance, Herrmann et al. (1997) show that an individual's intention to purchase a product increases with the amount of the discount offered by a seller. Consequently, price reductions are considered one of the most effective incentives a seller can offer to raise sales on online platforms (Becerril-Arreola et al., 2013). While cues in available reward options (e.g., early bird discounts and social proof) have proven successful, research has not unfathomed the effects of these cues in sold-out reward options.

Tan and Hwang Chua (2004) differentiate between two types of price reductions: plausible and exaggerated ones. Whereas customers perceive plausible price reductions as acceptable, as these reductions are within the price range that potential customers consider reasonable for sale, customers consider exaggerated price reductions less acceptable as these reductions fall outside of a customer's sensible price range. We thus suggest that potential backers infer different informational value from sold-out early birds that are on a moderate (i.e., plausible) discount in comparison to sold-out early birds with a high (i.e., exaggerated) discount. More specifically, we expect that backers infer that a sold-out early bird with a high discount (in contrast to a moderate discount) was rather due to monetary benefits rather than due to the desirability or value of the reward option content. Since the early bird is sold-out, the potential monetary benefits of the early bird offer are foregone and only the desirability of the phantom option's attributes remain. Consequently, we hypothesize that moderate discounts (in contrast to high discounts) lead to a higher selection share of the reward option with the same reward content as the sold-out early bird:

H3: *The presence of a high (vs. moderate) discount amount on a sold-out early bird decreases the selection of the available reward option with the same reward content.*

5.3.4 Interaction of Discount Amount and Social Proof

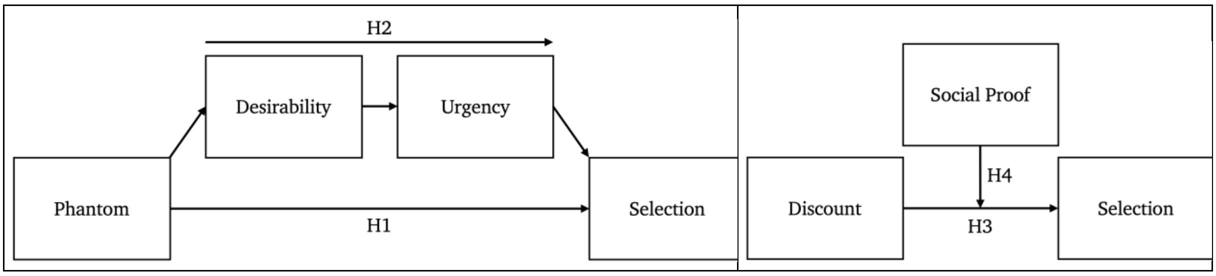
Social proof cues are another source from which customers derive information. These cues are implicit or explicit indicators that signal product demand and popularity (Cialdini, 1993;

Amblee and Bui, 2012). In simple terms, individuals usually infer that a behavior is right when a lot of people do it and tend to follow that behavior (i.e., bandwagon effect). Social inference refers to watching other's actions and deriving the meaning and implications for one's own decision, since other's behavior is assumed to be based on sound reasoning (Naylor et al., 2011). For instance, studies have shown that through this heuristic, customer determine the value of options (Burnkrant and Cousineau, 1975) as well as reasons to conform with previous selections (Goldstein et al., 2008; Zhang, 2010). In offline contexts, previous behavior of other customers is usually not directly observable, so that individuals consider the stock level of a product as a trace of previous demand, derive the popularity and value of the option, and then determine whether to select the product (Van Herpen et al., 2009; Parker and Lehmann, 2011). In online contexts, however, e-commerce companies use implicit social cues (e.g., banners) and explicit social cues (e.g., purchase counters). For instance, reward-based crowdfunding platforms indicate the number of backers per reward option and the total amount pledged in every campaign. As a result, this heuristic reduces the processing effort to handle and derive various information and plays an important role especially in low-involvement purchases (e.g., Zaichkowsky, 1985).

We thus investigate whether the notion of the number of backers influences and interacts with the discount amount of the phantom option as well. In reward-based crowdfunding, reward options usually indicate the number of backers who have already chosen the particular reward option to signal previous demand and create further demand. If the fundraiser decided to provide only a limited number of a certain reward option, the remaining supply of the reward option is mentioned. This is also true for sold-out options. Once the reward option is sold-out, the phantom option usually mentions the number of backers that have chosen the reward option before it has become unavailable. This number thus works as an explicit social proof cue that signals information in form of product demand and popularity (Cialdini, 1993; Amblee and Bui, 2012) and can help future backers in inferring product value. Consequently, the social proof cue can communicate the desirability and value of attributes that are existent or non-existent in the remaining reward option menu and represents an orientation towards which potential backers can conform and adjust their own selections (e.g., Rao et al., 2001; Goldstein et al., 2008; Zhang, 2010).

In H3, we argued that we expect that a high discount (in contrast to a moderate discount) leads to a lower selection share of the reward option with the same reward content as the sold-out early bird. Based on these expectations, if the sold-out early bird is offered at an exaggerated discount amount, potential backers rather consider the greatness of the deal instead of the desirability of the included features as a reason why the option has become sold-out. The experience of a missed opportunity to profit from the exaggerated deal is stronger the more backers have chosen the sold-out option. Consequently, we hypothesize that:

H4: *High (vs. low) social proof in the phantom option moderates the effect of the discount amount on reward option selection in such a way that the negative effect of a high discount becomes stronger.*



Note: (Left) direct effect of phantom options on reward option selection (H1) as well as the mediating roles of desirability and urgency (H2); (right) direct discount amount effect on reward option selection, given a phantom is present (H3) as well as the moderation effect of social proof (H4)

Figure 5-1: Research Model

To test the hypotheses in our research model (Figure 1), we used a multi-method approach comprising two independent studies (e.g., Venkatesh et al., 2016): We first conducted an online experiment (Study 1) with 512 participants simulating the pledging process of a reward-based crowdfunding campaign to establish the causal relationship and explore the underlying mechanisms that explain the phantom effect as well as the potential impact of discount amount and social proof cues (i.e., H1-H4). We then followed up with an observational study (Study 2) based on longitudinal data from 676 Kickstarter crowdfunding campaigns to analyse the external validity of our findings and further analyse the interaction effect of discount amount and social proof cues in the phantom option (i.e., H1, H3, and H4).

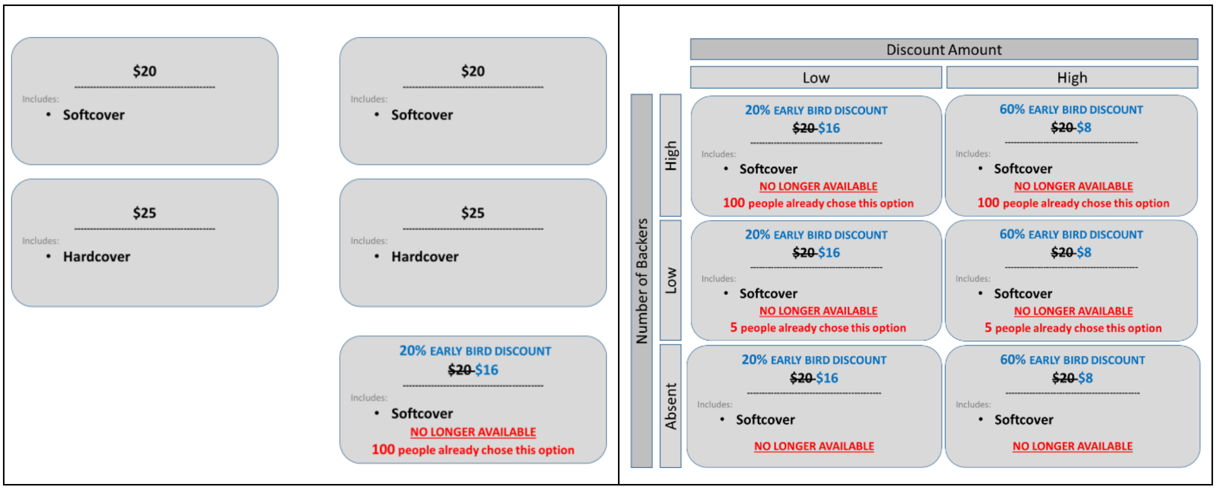
5.4 Study 1: Online Experiment

5.4.1 Participants

Consistent with previous studies on experiments about option choices in reward-based crowdfunding (e.g., Tietz et al., 2016; Simons et al., 2017), we recruited 699 participants through the crowdsourcing marketplace Amazon Mechanical Turk. Previous studies have demonstrated that survey results from Amazon Mechanical Turk workers have high reliability and can provide higher-quality data than student or online convenience samples (e.g., Steelman et al., 2014). Additionally, due it its nature, Amazon Mechanical Turk is a suitable platform to get in touch with Internet-savvy users, who are potential users of crowdfunding platforms. Moreover, we restricted participation to users who are U.S. residents with at least 95 percent approval rate to ensure data quality (Goodman and Paolacci, 2017).

5.4.2 Experimental Design, Treatments and Procedures

To test the phantom effect in crowdfunding campaigns and therefore our hypotheses, we employed a 2 (DiscountAmount: moderate vs. high) x 3 (SocialProof: absent vs. low vs. high) between-subject online experiment with an additional hanging control group that contained no phantom option and thus no discount and social proof cue. By conducting an online experiment, we could avoid the abundance of different cues and isolate the individual impact of the phantom effect as well as the effects of discount amount and the number of backers. Since we expected that not all participants would have actively participated in reward-based crowdfunding before, we avoided typical crowdfunding jargon (e.g., "pledge" and "back") and instead used more common words (e.g., "buy" and "contribute").



Note: Control condition with no phantom option as well as condition with example of phantom option: high discount with high number of previous backers (left); display of the phantom options used in the six experimental conditions (right)

Figure 5-2: Reward Option Menus

The treatments were solely manipulated based on phantom options that were shown to the participants in the reward option menu (Figure 2). The experimental design of the six conditions as well as control condition is based on our definition of early bird options, which are sold-out reward options that are equivalent to another available reward option in the reward option menu but differ in price. While a sold-out early bird can be presented without a social proof cue, a sold-out early bird without a discount cue would cause confusion as it defies the purpose.

We framed the online experiment as a pledging process on a fictional reward-based crowdfunding platform. More specifically, we narrowed the experiment to the stock-out situation in which a reward option in form of an early bird is sold out. The reward option menu was designed similar to the ones that are found in practice: We divided the menu into two sections based on the availability or unavailability of the reward options. Within these sections, the reward options were ascendingly sorted based on pledging amount. To further frame the experiment, we created a campaign with the intention to fund the publishing of a book called Augie and the Green Knight (Kickstarter, 2018), which also represents publishing as one of the most common project categories on reward-based crowdfunding platforms (Kickstarter, 2018). The participants went through an experimental procedure consisting of five main steps as depicted in Figure 3.

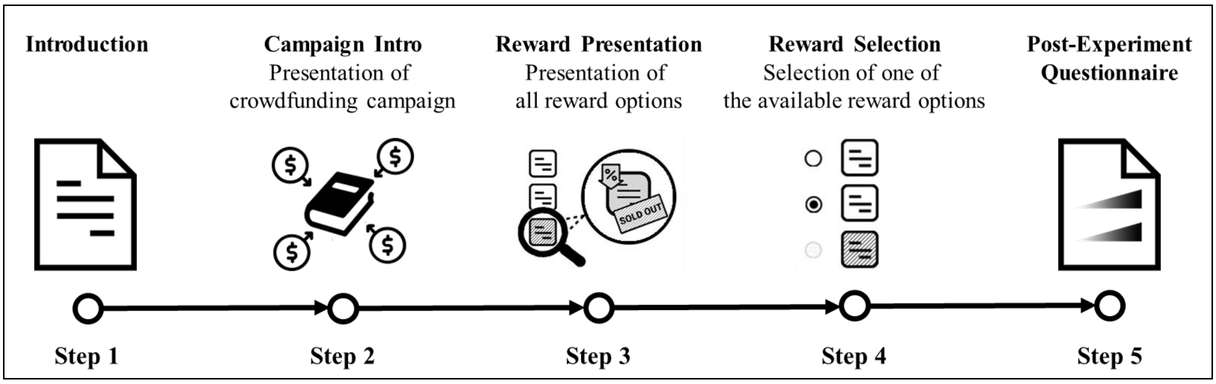


Figure 5-3: Experimental Procedure During the Online Experiment

5.4.3 Manipulation of Independent Variables

To derive adequate rewards for our experiment that are not confounded by unwanted effects, we first have to identify which reward options we can display. Crowdfunding campaigns that fund books are primarily restricted in the content of rewards due to the nature of the product. Nowadays, the most common forms of books in an increasing order based on price are ebooks, softcover books, hardcover books, and audiobooks. Since the four common rewards differ in the needed senses to perceive the story (visual or auditive) and difficulty to replicate and transport it (electronically or physically), we chose to offer two reward options, namely, a softcover book and a hardcover book. Thus, the two reward options differed only in two features: cover quality and price. The price was \$20 for the softcover book and \$25 for the hardcover book, with \$25 representing the most common reward option price on Kickstarter (Kickstarter, 2018). The early bird was a reward option that offered the softcover book as well, but at a reduced price.

Because of the ascending nature based on price and the two separate sections for available and unavailable reward options, the vertical order and content of the three reward options did not differ between the conditions. However, the display of the presence as well as of the price reduction and the social proof cues were dependent on the assigned conditions (Figure 2).

In accordance with the findings of Tan and Hwang Chua (2004), the discount amount on the sold-out early bird was either moderate (i.e., 20%) or high (i.e., 60%). The social proof influence was the number of backers, which was either absent, low (i.e., 5) or high (i.e., 100). These numbers were based on percentiles of sold-out early birds on Kickstarter, whereby the low number of backers approximately represents the 10 percentile and the high number the 90 percentile (dataset is equivalent to the one used in Study 2).

5.4.4 Variables Measured

Our core dependent variable was the Selection share of the reward options, indicating any change in preferences of the participants towards the available reward options. Thus, the selection was binary and dependent on whether the participant chose the softcover or the hardcover book option. Moreover, based on adjusted items, we measured our mediators Desirability (Huang and Zhang, 2016) and Urgency to buy (Gupta, 2013) with regard to the softcover book as well as various control variables: Age, Gender, Income, ProductInvolvement (PI) from Zaichkowsky (1985), NeedForUniqueness (NFU) from Tian et al. (2001), NeedForConformity (NFC) from Bearden and Rose (1990), and SalesProneness (SP) from Lichtenstein et al. (1995). We assessed all aforementioned variables based on scales with items on a 7-point Likert-type scale with anchors ranging from strongly disagree (1) to strongly agree (7). We averaged the items of all constructs that used several items in their scale, as they displayed good psychometric properties with regard to high internal consistency as well as convergent and discriminant validity (Fornell and Larcker, 1981; Awad and Krishnan, 2006). Moreover, we assessed whether the participant had CrowdfundingExperience (CE) and thus have pledged on a crowdfunding platform before. Also, we identified participants who had CampaignKnowledge (CK) and thus have heard of the campaign before, because we used a real crowdfunding campaign. Also, we used one attention check, four manipulation checks, and items of the Popularity scale from Van Herpen et al. (2009) to make sure that participants paid attention and that our manipulations were successful. Lastly, we assessed participants' PerceivedRealism.

5.4.5 Sample Descriptives and Manipulation Checks

699 participants from Amazon Mechanical Turk started and finished the online experiment including the post-hoc questionnaire. Out of these, we removed 183 respondents because they failed the attention or one of our four manipulation checks. Additionally, we removed four participants who indicated that they find the simulation strongly unrealistic. Of the resulting 512 subjects, 47% were females and 53% were males. Their average age was 36 years. The most frequent income was $1,000-1,999. All participants were U.S. residents. 32 percent of all participants had pledged on a crowdfunding platform before.

Since we adopted established constructs for our measurement, we conducted confirmatory factor analysis to assess the instruments' convergent and discriminant validity for the dependent variables (Levine, 2005). The constructs were assessed for reliability using Cronbach's alpha (Cronbach, 1951). All of our measured constructs exceeded 0.7 (Nunnally and Bernstein, 1994). Furthermore, composite reliability of all constructs were larger than the minimum threshold of 0.7 (Hair et al., 2011). Values for average variance extracted (AVE) surpassed the variance due to measurement error for that construct (i.e., AVE surpassed 0.5). Consequently, all constructs met the norms for convergent validity. Additionally, to check for adequate discriminant validity, all square roots of AVE from each construct exceeded the variance shared with other constructs in the model (Fornell and Larcker, 1981).

5.4.6 Results

5.4.6.1 Hypothesis 1: Phantom Effect

In H1 we suggested that the presence (vs. the absence) of a sold-out early bird results in a higher request for the available reward option with the same content (phantom effect). Based on our sample of 512 respondents, we performed a binary regression analysis on the dependent variable Selection of the available reward options. We coded the choice of the reward option with the softcover book as 1 and as 0 when the participant chose the hardcover book. We entered all controls and the Phantom manipulation by comparing all of the six phantom conditions against the control condition (Table 1, Block I).

Regarding H1, our findings in Block I demonstrate that the Phantom manipulation had a significant influence on the Selection share of the reward options ($b = 0.796$, Wald statistic (1) $= 8.847$, $p < 0.01$). More specifically, participants were almost twice as likely to select the available softcover option. The results thus support H1, predicting that phantom options influence backers in their selection decision.

	Block I (H1)			Block II (H3)			Block III (H4)		
	Coef.	SE	Exp(B)	Coef.	SE	Exp(B)	Coef.	SE	Exp(B)
Intercept	1.894	1.547	6.647	2.231	1.613	9.311	-0.018	2.254	0.982
Manipulation									
Phantom††	0.796**	0.268	2.217						
DiscountAmount†				-0.404*	0.204	0.668	-0.452	0.345	0.636
SocialProof†							-0.095	0.370	0.909
DiscountAmount x *Social Proof††*							0.217	0.507	1.242
Controls									
SocialProof††				-0.025	0.216	0.975			
Age	-0.007	0.008	0.993	-0.007	0.009	0.993	-0.004	0.010	0.996
Gender	-0.188	0.200	0.829	-0.300	0.217	0.741	-0.378	0.269	0.685
Income	0.023	0.053	1.023	0.037	0.057	1.038	0.033	0.068	1.034
CE	-0.427*	0.205	0.653	0.328	0.223	1.388	0.560*	0.274	1.751
CK	0.696	0.623	2.005	-0.351	0.640	0.704	0.653	0.954	1.921
PI	-0.272***	0.059	0.762	-0.221***	0.062	0.802	-0.141	0.077	0.869
SP	0.046	0.080	1.047	0.040	0.085	1.040	-0.006	0.111	0.994
NFU	-0.060	0.066	0.942	-0.027	0.071	0.973	0.034	0.088	1.034
NFC	0.020	0.068	1.020	0.007	0.073	1.007	-0.091	0.091	0.913
-2 Log Likelihood	652.334			561.652			372.039		
R^2	0.108			0.070			0.063		
$\chi2$	42.935***			23.430*			13.762		
Observations	512			437			288		

Note: * p<0.05; ** p<0.01; *** p<0.001, n=512; S.E.= Standard Error; † low/moderate =0, high=1; †† absent=0, present=1; CE = CrowdfundingExperience; CK = CampaignKnowledge; PI = Product Involvement; SP = Sales Proneness; NFU = Need for Uniqueness; NFC = Need for Conformity

Table 5-1: Binary Logistic Regression on Reward Option Selection

5.4.6.2 Hypothesis 2: Mediation Effect

While H1 focusses on demonstrating the phantom effect, in H2, we claimed that the phantom effect operates through a change in the perception of the desirability of available rewards, as well as indirectly through an increase of the urgency to buy. To verify the mediation effect, we conducted a bootstrap moderation analysis with 10,000 samples and a 95% bias-corrected confidence interval (Hayes, 2017, model 6) to test whether Desirability and Urgency to buy serially mediate the phantom effect.

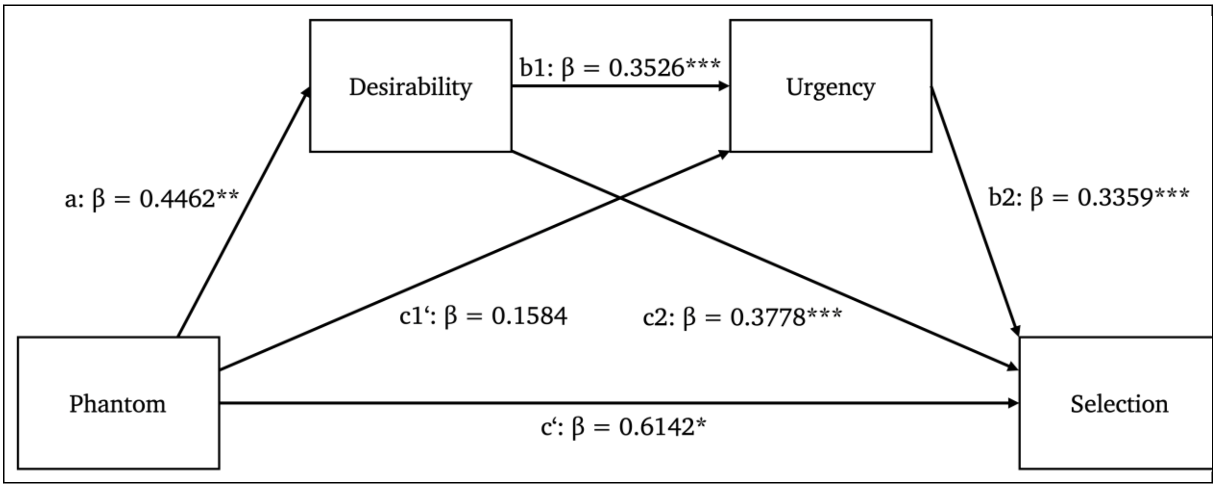


Figure 5-4: Serial Mediation of Desirability and Urgency

First, we find that the presence of a Phantom option increased the Desirability of the softcover book in the interaction ($\beta = 0.4462$, $t = 2.7847$, $p < 0.01$) and that this Desirability, in turn, increased the likelihood (controlling for stated urgency to buy) that the softcover book was selected ($\beta = 0.3378$, $z = 4.3184$, $p < 0.001$). The 95% CI for the indirect effect of Desirability excluded zero (paths a x c2 = -0.1686; 95% CI: [0.3500, 0.0434]), hence demonstrating that Desirability mediates the Phantom effect (even after we accounted for measured Urgency). Consequently, the phantom effect operates by making the rewards of the phantom options seem more desirable (Figure 4).

Second, we also hypothesized that Urgency would increase by the presence of a Phantom mediated by Desirability. We find that the Phantom significantly increases Urgency to buy the softcover book through a mediation through Desirability ($\beta = 0.326$, $t = 8.0509$, $p < 0.001$), but does not do so directly ($\beta = 0.1584$, $t = 1.0010$, $p > 0.05$). Moreover, the Urgency increased the likelihood to select the softcover book ($\beta = 0.3359$, $z = 4.0192$, $p < 0.001$). To assess whether these effects provide additional explanatory evidence, we also calculated the conditional indirect effects through both mediators. Consistent with our beliefs, we found that the 95% CI excluded zero (serial path a x b1 x b2 = 0.528; 95% CI: [0.0136, 0.1210]). Lastly, we failed to find evidence for an indirect effect through only Urgency (paths a x c2 = 0.0532; 95% CI: [-0.0340, 0.1760]), suggesting that the presence of the Phantom only improves the Urgency if the backer perceives the product more desirable.

5.4.6.3 Hypothesis 3: Effect of Discount Amount

In H3, we hypothesized that the presence of a high (vs. moderate) discount amount on a sold-out early bird decreases the selection of the available reward option with the same reward content. To consider and include only the conditions with a phantom option and discount amount cues, we removed the control condition without any phantom option, resulting in a sample of 437 subjects. We performed a binary regression analysis on the dependent variable Selection of the available reward options (Table 1, Block II). We entered all controls and added the DiscountAmount manipulation and a control variable concerning the effect of the presence or absence of a SocialProof cue and thus compared all of the three high discount amount conditions against the three moderate discount conditions (Table 1, Block II).

Regarding H3, our findings demonstrate that the DiscountAmount manipulation had a significant influence on the Selection share of the reward options ($\beta = -0.404$, Wald statistic (1) $= 3.917$, $p < 0.05$). More specifically, participants were about 33 percent less likely to select the available softcover option when the DiscountAmount was high instead of moderate. Consequently, the results support the claim H3 that the DiscountAmount in phantom options influence pledgers in their Selection decision.

5.4.6.4 Hypothesis 4: Moderation Effect of Social Proof

In H4 we suggested that a high (vs. low) social proof cue in the phantom option moderates the effect of the discount amount on reward option selection in such a way that the negative effect of a high discount becomes stronger. To isolate the effect and only consider phantom conditions that showed both DiscountAmount and SocialProof cues, we excluded the control condition and the two conditions with only the DiscountAmount cue. Therefore, our sample size consisted of 288 subjects. We performed a binary regression analysis on the dependent variable Selection of the available reward options.

Our findings in Block III demonstrate that the Interaction had no significant influence on the Selection share of the reward options. We also conducted a bootstrap moderation analysis with 10,000 samples and a 95% bias-corrected confidence interval to test whether SocialProof moderates the effect of DiscountAmount (Hayes, 2017, model 1) . The results of our moderation analysis show that the effect of a high DiscountAmount on reward option Selection is not significantly moderated by SocialProof, such that there is no significant difference when a high number of backers is present (effect = -0.2354, standard error = 0.3776, $p > 0.1$, 95% bias-corrected confidence interval (CI) = [-0.9755, 0.5048]) compared to a low number of backers (effect = -0.4522, standard error = 0.3448, $p > 0.1$, 95% bias-corrected confidence interval (CI) = [-1.1279, 0.2235]). Therefore, we could not find evidence to support H4.

5.5 Study 2: Observational Study

5.5.1 Purpose of Study 2

We note that our online experiment in Study1 was constrained to a simulation with limited ecological validity, restricted by a relatively small sample and a single project category. Moreover, although Study 1 confirmed the existence of the phantom effect as well as the underlying explanatory mechanism based on desirability and urgency, a number of questions remain unanswered primarily with regard to the effects of discount amount and social proof. We intend to address these questions in Study 2, corroborating the high internal validity of the first study's experimental design within a more generalizable context.

First, though we gathered strong evidence that a moderate discount amount strengthens the phantom effect more than a high discount, this result only provides us a peek into the potentially far more complex relationship between the amount of discount for the phantom option and backers' decision-making. Given the restrictions of an online experiment, we were unable to test a broad range of different discount amounts below or above the moderate condition. As a consequence, we gained little insight into optimal levels of discount. For instance, as the amount of discount rises, its beneficial impact will reach a maximum and then decrease once the discount turns from a plausible one into an exaggerated one (e.g., 60%). Then again, a smaller discount (e.g., 5 percent) is inconsistent with the claim of an early bird offer being a "good deal", so that potential backers will most likely disregard the cue (Inman et al., 1997). Thus, in order to get a more fine-grained understanding on the role of discount in this context, we investigate whether a curvilinear relationship exists between the amount of discount and the phantom effect.

Second, the first study failed in finding significant effects of social proof cues, which might be due to inappropriate levels of social proof in the two experimental conditions. Again, the data we gathered for Study 2 allows for a more detailed comprehension of the effect that social proof cues might have on the relationship between the discount amount and the phantom effect.

5.5.2 Data and Methods

5.5.2.1 Data Source and Sample Construction

For the second study, our sample is drawn from Kickstarter, one of the world's largest reward-based crowdfunding platform. Since the platform's launch in 2009, over $4 billion has been invested by more than 15 million individuals, successfully funding over 150,000 projects (Kickstarter, 2018). Using a self-developed web crawler, we collected a daily time series dataset that contains data on 23,008 Kickstarter campaigns that started and ended within the period from December 23, 2017 to July 9, 2018. For each campaign, the dataset contains detailed information on all of the campaign's time-invariant characteristics (e.g., project category, title, description, and funding goal) as well as time-variant performance indicators (e.g., total funds raised and number of times each reward option has been selected).

We perform the following procedures to construct the sample: We first excluded campaigns that were canceled by the project creator as well as campaigns that were suspended or removed by Kickstarter due to, for instance, copyright infringements. To identify campaigns that contain at least one phantom option (i.e., a sold-out early bird reward with an equivalent undiscounted and unlimited alternative), the reward options were computationally compared within each of the 20,516 campaigns. The following three conditions were required to safely identify campaigns containing at least one phantom option: (1) A sold-out reward option exists that was limited in quantity and (2) a reward option exists within the same campaign that has exactly the same description as the sold-out reward option. Alternatively, a reward option exists within the same campaign that has a title that contains the string "early bird" and the Levenshtein distance[4] for the description is 10 or smaller in comparison to the description of another reward option in the same campaign[5]. (3) The alternative, not sold-out reward option is unlimited in quantity and more expensive than the phantom option. After applying these three conditions, a total of 784 campaigns were left in our dataset. To isolate the hypothesized effects, we excluded campaigns that contained more than one phantom option and removed a small number of outliers (i.e., number of backers for the phantom option exceeded 300) to avoid that few extreme observations confound the results. The final dataset contains 676 campaigns.

5.5.2.2 Dependent Variable

For this study, we define the dependent variable Selection as the number of backers who have chosen the equivalent alternative to the phantom option divided by the average number of backers per reward option. For instance, considering a campaign that has received a total of 100 pledges from backers across five reward options of which 30 backers have selected the equivalent alternative to the sold-out phantom option. In this example, the average number of pledges per reward is thus 20 and Selection equals 1.5 (i.e., 30 divided by 20). A value below

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[4] The number of deletions, insertions, or substitutions required to transform the text string of a reward-option description into another reward-option description in the campaign is 10 or smaller.

[5] As a robustness test, we only included campaigns in our analysis that satisfied the first, more restrictive condition (exact same description). These results confirmed our findings.

1 thus indicates that the alternative to the phantom option has attracted a below-average number of backers.

$$\text{Selection}_{it} = (\text{Backers}_{it} \times \text{Rewards}_{i}) \,/\, \text{TotalBackers}_{it} \qquad (1)$$

Backers_{it} is number of backers for the equivalent alternative to the sold-out phantom option for a specific campaign (i) on a single day (t). Rewards_{i} is the campaign-specific number of rewards, which is static over time in our sample. TotalBackers_{it} is the total number of backers for a specific campaign (i) on a single day (t). Consequently, the variable Selection allows us to measure how the existence of a phantom alternative alters backers' individual decision-making within every single campaign.

5.5.2.3 Explanatory and Moderating Variables

The explanatory, dichotomous dummy variable Phantom turns from zero to one on the day the early bird is sold out and thus becomes a phantom option. DiscountAmount, is equal to the discount amount in percent between the price of the phantom option and of the equivalent undiscounted alternative. The moderating variable SocialProof indicates the number of the early bird reward option that were available before it was sold out (i.e., the official number of backers that were able to acquire the option).

5.5.2.4 Control Variables

We incorporate a number of additional project-level time-variant and -invariant control variables in our model to remove their confounding impacts on backers' decisions. Prior studies have shown that all of the listed control variables may impact crowdfunding success (e.g., Kuppuswamy and Bayus, 2013; Mollick, 2014; Wessel et al., 2016). As our dataset spans approximately seven months including the Christmas and holiday season, we created dummy variables for the specific month in which the campaign was launched to control for unobservable time-varying seasonality effects (Seasonality) (Kuppuswamy and Bayus, 2013). We also constructed dummy variables that represented in which of the 15 main categories on Kickstarter (e.g., art, design, or technology) the campaign was launched (Kuppuswamy and Bayus, 2013; Wessel et al., 2016). Duration is a log-transformed measure that indicates how many days the campaign accepts funding (Kuppuswamy and Bayus, 2013; Wessel et al., 2016). DaysLeft controls for possible deadline effects (i.e., effects that emerge through the closeness of a deadline) by considering the remaining days the campaign is open and accepts funding (Kuppuswamy and Bayus, 2013). Goal is the log-transformed measure of the funding goal in USD specified for the campaign (Kuppuswamy and Bayus, 2013). Successful is a dummy variable that is equal to one if the campaign has surpassed its funding goal. AvgRewardPrice is the natural logarithm of the average price of rewards offered (Kuppuswamy and Bayus, 2013). Video is a dummy variable that specifies whether the project creator has uploaded a video for the campaign (Kuppuswamy and Bayus, 2013; Wessel et al., 2016). Updates and Comments are the log-transformed measures that are one plus the number of updates the creator has posted for the project and one plus the number comments left by backers during the active campaign, respectively (Mollick, 2014).

5.5.2.5 Model Specification

To test our hypotheses H1, H3, and H4 based on the quantitative data gathered from Kickstarter, we employ a random effects model, which assumes that unobserved individual effects are uncorrelated with the included regressors[6]. The Hausman specification test ($p > 0.05$) suggests that the use of a fixed effects model, where the time-invariant, campaign-specific heterogeneity is absorbed by the campaign's fixed-effects, is not appropriate and thus suggests to estimate the model under use of random effects (Hausman and Taylor, 1981). Furthermore, we have an unbalanced panel (i.e., campaigns are not observed over the same time periods) and a "large N small T" panel structure, meaning that we observe a large number of campaigns over a rather small number of periods. Both these conditions suggest that a random effects model is more appropriate (Chellappa et al., 2010). Therefore, we derive the following model specification for our baseline regression:

$$y_{it} = \alpha + u_i + \beta x_{it} + \varepsilon_{it} \tag{2}$$

y_{it} is the dependent variable Selection for each campaign (i) on a single day (t). u_i is the campaign-specific random effect. Our independent variables Phantom and DiscountAmount, the moderating variable SocialProof, and our set of control variables are represented by βx_{it}, while ε_{it} is the error term.

5.5.3 Results

Table 2 presents the descriptive statistics for all variables included in our models, while Table 3 and 4 show the results of the regression analysis under the use of random effects for H1 and H3/H4, respectively. In Table 3, Model 1-1 includes the before/after dummy Phantom indicating whether the phantom option existed. To model the dynamic effects and to rule out

[6] As a robustness test, we use the percent of total investments that the alternative to the phantom option receives as the dependent variable and estimate this model specification using a Tobit model designed to model continuous, bounded dependent variable. The results using this alternative econometric model are in line with those reported here.

rival explanations, we created a set of time-related dummies for the five days before and after as well as on the day Phantom turned from zero to one. Observations in Model 1–2 are thus restricted to be within an 11-day time period.

	Mean	Std. Dev.	Min	Max
Selection	1.8872	1.9083	0	15.0986
DiscountAmount	20.6909	12.9316	0.45	66.67
SocialProof	35.6287	50.492	1	300
Duration [a]	3.3332	0.3587	1.3863	4.0943
Goal [a]	8.0638	1.8343	1.6094	13.5924
Successful	0.2860	0.4523	0	1
AvgRewardPrice [a]	4.4983	1.2815	1.6740	10.3994
Video	0.6420	0.4799	0	1
Updates [a]	1.5721	0.8077	0	3.9120
Comments [a]	2.2455	1.6875	0	7.2951

Note: [a] Variable is log transformed

Table 5-2: Descriptive Statistics.

In Table 4, Model 2-1 is the baseline model and consists only of the control variables. Model 2-2 and 2-3 add DiscountAmount and its square term, respectively. Models 2-4 and 2-5 add the moderating variable SocialProof and its interactions with the linear and quadratic terms of DiscountAmount. We examine and compare the explanatory power of the models based on their log likelihoods. Based on a likelihood ratio test comparing Model 2-2 to the controls-only baseline model (Model 2-1), we find no significantly improved model fit. However, Models 2-3 to 2-5 significantly improve model fit, with Model 2-5 being the best fitted model.

	ΔSelection	
Model	(1-1)	(1-2)
Control variables		
Seasonality (dummies)	Included	Included
Category (dummies)	Included	Included
Duration	0.3792	-0.184
DaysLeft	-0.0033	0.0199
Goal	0.0175	0.0144
Successful (1/0)	-0.2497	0.5744
AvgRewardPrice	0.1649	0.1803
Video (1/0)	-0.5611^{*}	-0.189
Updates	0.3898^{***}	0.1792
Comments	-0.0972	-0.1432
Explanatory variables		
Phantom	1.61^{***}	
T-5		0
T-4		0.1655
T-3		0.0292
T-2		0.1192
T-1		-0.09701
T		0.7591^{**}
T+1		2.35^{***}
T+2		2.39^{***}
T+3		2.496^{***}
T+4		2.545^{***}
T+5		2.515^{***}
Constant	-0.7973	-0.4712
σ_u	2.256^{***}	2.062^{***}
σ_e	3.585^{***}	2.472^{***}
Log likelihood	-34545	-9126
Number of campaigns	676	676
Observations	12,567	3,709

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5-3: Linear Random-Effects Regression on ΔSelection

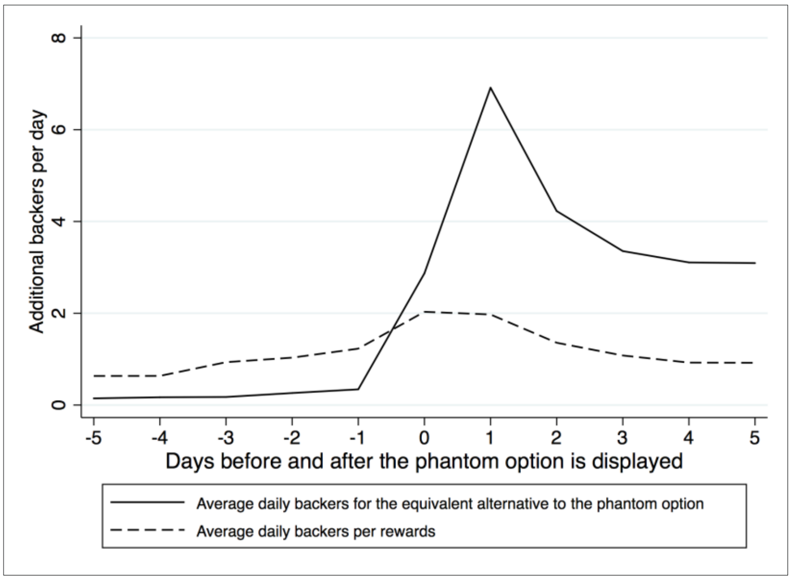

Figure 5-5: Average Backers Before and After Phantom Option Becomes Available

5.5.3.1 Hypothesis 1: Phantom Effect

In Hypothesis 1, we suggested that the presence of a sold-out early bird results in a higher request for the equivalent and still available reward option (phantom effect). To test H1, we introduce the dummy variable Phantom in Model 1-1, which turns to one once the early bird option is sold out and becomes a phantom. Estimates from this model support the hypothesis. The coefficient of the Phantom variable is positive and significant ($\beta = 1.61$, $p < 0.001$). Consequently, the results suggest that the phantom option significantly impacts backers' decision-making in favor of the reward option that is equivalent to the phantom option.

When looking at the dynamic effects in model 1-2, we can also observe no significant coefficients before the phantom option exists. However, at day T, the first day the phantom option exists, and on all following days, the coefficients are positive and significant. This, again, confirms the significant shift in backers' decision-making towards the equivalent alternative to the phantom option. Figure 5 further illustrates the per-day changes in additional backers before and after the phantom option exists. The alternative to the phantom option is selected by a below-average number of backers before the phantom option is displayed. However, once the phantom exists, the performance is significantly above average.

5.5.3.2 Hypothesis 3: Effect of Discount Amount

For H3, we hypothesized that a moderate discount amount (in contrast to a high discount amount) displayed in the phantom option will lead to a higher selection share of the reward option that is equivalent to the phantom option. The insignificant coefficient for DiscounAmount in model 2-2 suggests that no linear negative relationship exists between amount of discount and Selection that would support H3. However, as previously discussed, an inverted U-shaped relationship may exist between the variables as extremely low or high amounts of discounts for the phantom option may inadvertently affect backers' decision-making. Model 2-3 (Table 4) shows that DiscountAmount is positive and significant, and that the square of DiscountAmount is negative and significant. However, though necessary, a significant coefficient for DiscountAmount2 alone is not sufficient to establish a quadratic relationship. We thus follow the three-step procedure suggested by Lind and Mehlum (2010) to formally confirm the existence of the inverted U-shaped relationship: First, our results show that the coefficient of the square of DiscountAmount is negative and significant ($\beta = -0.0005$, $p < 0.001$). Second, the slope must be sufficiently steep at both ends of the data range. As DiscountAmount ranges between 0.45 and 66.67, we test at DiscountAmount = 5 and DiscountAmount = 60 whether the slope is positive and significant at the low end as well as negative and significant at the high end. The results confirm the positive slope at the low end ($p < 0.001$) and the negative slope at the high end ($p = 0.001$). Third, the turning point of the curve needs to be located well within the observed data range. Taking the first derivative of the regression equation and setting it to zero reveals that the turning point is at 33.84 percent discount and its 95 percent confidence interval is within the observed range. To facilitate interpretation, we graphed model 2-3 over the range of DiscountAmount (0-60), keeping covariates at their means. Figure 6 (left) shows a nonlinear relationship of DiscountAmount with Selection.

We therefore find support for H3 and can confirm the results from our experiment by showing that a plausible discount in the range of 20 to 40% leads to a higher selection share of the reward option that is equivalent to the phantom option compared to extremely low or high amounts of discounts.

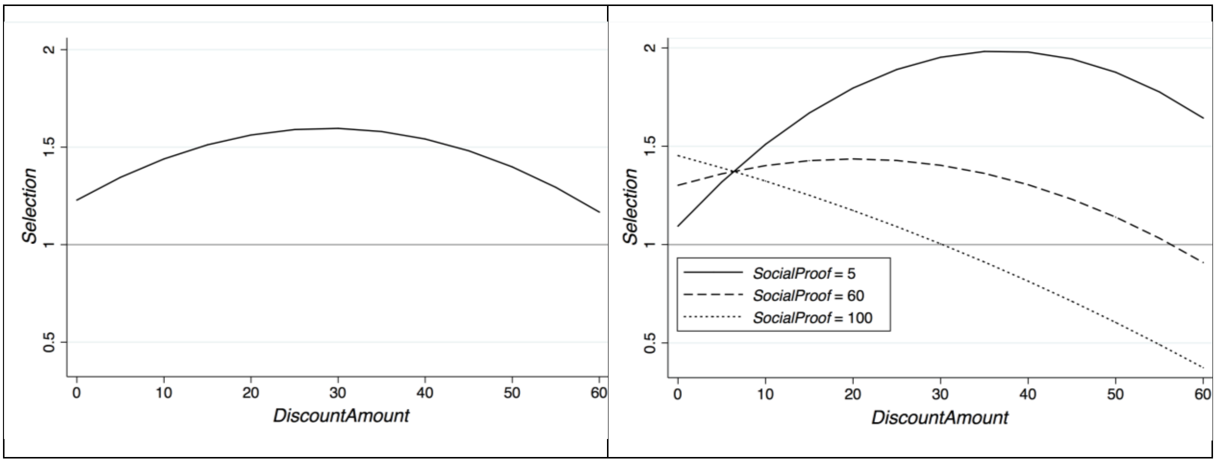

Figure 5-6: Effects of DiscountAmount (Model 2-3) and SocialProof (Model 2-5)

	Selection				
Model	(2-1)	(2-2)	(2-3)	(2-4)	(2-5)
Control variables					
Seasonality (dummies)	Included	Included	Included	Included	Included
Category (dummies)	Included	Included	Included	Included	Included
Duration	-0.3002	-0.3024	-0.3044	-0.2786	-0.296
DaysLeft	-0.0140***	-0.0140***	-0.0141***	-0.0137***	-0.0138***
Goal	0.0245	0.0243	0.0328	0.0924	0.0974
Successful (1/0)	-0.0604	-0.0604	-0.0597	-0.0600	-0.0637
AvgRewardPrice	0.0002	0.0026	0.0172	-0.0175	-0.0037
Video (1/0)	0.1062	0.1061	0.1102	0.1343	0.1442
Updates	0.4227***	0.4228***	0.4234***	0.4212***	0.4228***
Comments	0.0758***	0.0762***	0.0766***	0.0871***	0.0880***
Explanatory variables					
DiscountAmount		0.0018	0.0347***	0.0348***	0.0512***
DiscountAmount²			-0.0005***	-0.0005***	-0.0007***
SocialProof				-0.0041***	0.0038
DiscountAmount x *SocialProof*					-0.0006***
DiscountAmount² x *SocialProof*					5.77e-06*
Constant	2.042***	2.005***	1.517*	1.229*	0.958
σ_u	1.532***	1.535***	1.536***	1.53***	1.539***
σ_e	0.5292***	0.5291***	0.5287***	0.5285***	0.5278***
Log likelihood	-11622	-11622	-11614	-11606	-11594
Number of campaigns	676	676	676	676	676
Observations	12,780	12,780	12,780	12,780	12,780

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5-4: Linear Random-Effects Regression on Selection

5.5.3.3 Hypothesis 4: Moderation Effect of Social Proof

In H4, we suggested that high (vs. low) social proof in the phantom option moderates the effect of the discount amount on reward option selection in such a way that the negative effect of a high discount becomes stronger. This would suggest that with higher values for SocialProof, the turning point of the curvilinear relationship between DiscountAmount will move to the left and/or the shape of the relationship will be flatter. We first test whether the turning point of the curve moves to the left as SocialProof increases. Taking the first derivative of the regression equation reveals that the turning point is at 37.06 percent discount if SocialProof = 5. However, the turning point for SocialProof = 60 is at 20.12 discount, for SocialProof = 100 the turning point is less than zero and thus out of the observed data range. Furthermore, the coefficient of the interaction term between DiscountAmount and SocialProof in Model 2-5 is negative and significant (β = -0.0006, $p < 0.001$), while that of the interaction term between DiscountAmount2 and SocialProof is positive and significant (β = 5.77e-06, $p < 0.05$). This suggests that a flatting of the curve occurs, meaning that the curvilinear relationship between DiscountAmount and Selection is weakened by the moderator SocialProof (Haans et al., 2016). Figure 6 (right) illustrates the effect of an increase in SocialProof from 5 (10th percentile based on the dataset use for Model 2-5) to 60 and to 100 (90th percentile). We also calculate the slopes to the right of the turning point as SocialProof increases. These are also less negative compared to model 2-3, providing further evidence that the curve flattens as SocialProof increases. These results thus provide support for H4.

5.6 Discussion

This piece of research aimed to examine and reveal the phantom effect on backers' option selections in reward-based crowdfunding. We also sought to advance our comprehension on why the effect emerges and how cues in the sold-out option influence this effect. Our findings support our premise that phantom reward options influence backers' selections. Specifically, we show that potential contributors select an available option that is equivalent to the sold-out one with regard to reward content. This effect can be explained by the increased desirability of and urgency to buy the still available reward content. Moreover, we show that an inverted U-shaped relationship exists between the amount of discount and backers' selection behaviors. More precisely, a moderate discount on the phantom option steers significantly more backers towards the equivalent but undiscounted reward option compared to small or exaggerated discount levels. Finally, social proof cues mitigate the relationship between the amount of discount and the phantom effect, so that a higher number of backers for the phantom option lead to a less positive effect of the amount of discount on the backers' selection behaviors. Thus, our research demonstrates that phantom options can change backers' option selections and, therefore, can work as a strategic nudge to increase funding success.

5.6.1 Theoretical Contributions

Our paper contributes to research primarily by providing a novel perspective on the nascent area of designs of reward option menus, but has counterintuitive impetus for entrepreneurs and e-commerce as well.

First and foremost, following the call to further explore nudging in digital contexts (Weinmann et al., 2016), we address the theoretically and practically neglected effect of sold-out reward options by investigating phantom options as prospective digital nudges in reward-based crowdfunding and showing how they can significantly influence backers' selection outcome. Our two studies show that if crowdfunding platforms display sold-out reward options, the features of these phantom options with regard to reward content impact backers' selection of available reward options. Furthermore, we provide an answer for the discrepancy for why Joenssen and Müllerleile (2016) found a general negative impact of scarcity cues in reward-based crowdfunding platforms, although Weinmann et al. (2017) discovered a positive effect of scarcity in general. We reconcile mixed and inconclusive findings by providing an alternative explanation based on the consideration of displayed and influencing phantom options. Consequently, we contribute to previous research on context effects in general and specifically in the domain of reward-based crowdfunding (Tietz et al., 2016; Simons et al., 2017) and provide evidence above and beyond the already explored decoy and compromise effects, expanding research on how users consider phantom options.

Second, we depart from prior research on phantom theory by investigating how cues (i.e., discount amount and social proof) of the sold-out reward options affect selection decisions. This investigation has become possible and practically highly relevant due to the newly arising context of reward-based crowdfunding in which phantoms are common and not the exception. While studies on phantom effects in various fields have considered product similarity, chooser's characteristics, or even the presence of discount cues in options, this research is the first to consider attributes in the unselectable option. We revealed an inverted U-shaped relationship between discount amount and backers' selection behavior, in that a moderate (vs. an exaggerated or low) discount amount cue on the phantom option steers significantly more backers towards the equivalent but undiscounted reward option.

Third and lastly, we demonstrate that even attributes in the phantom options do not exist in a vacuum and are influenced by other attributes in the context. We reveal an interaction effect of most common reward-based crowdfunding cues in that social proof moderates the curvilinear impact of the discount amount due to the adequacy and consistency of the presented information. Thus, our results indicate that researchers analysing the impact of reward option designs need to comprehend and consider all relevant cues to identify and assess not only their isolated effects but also their effects in the context of and in coexistence with other moderating influences.

5.6.2 Implications for Practice

From a managerial point of view, our studies offer insights for project creators as well as for platform operators. Project creators use early bird offers abundantly in reward-based crowdfunding, as these options can accelerate initial demand and create momentum (Kickstarter, 2018). Weinmann et al. (2017) demonstrated that backers are more likely to select reward options that are scarce so that scarcity cues can be used as a strategic nudge. Yet, providing reward options limited in supply may harm the fundraising project in total once the supply is exhausted and the reward options become a phantom. Therefore, the once positive early bird effect that created momentum in the initial steps of the campaign may rebound once the early bird turns into a phantom and keeps influencing backers' decision-making. Consequently, creators need to weigh the benefits of the accelerated demand during the early days of a crowdfunding campaign against the possible negative influence of the phantom option. Moreover, entrepreneurs can try to combine the beneficial effects of early birds when they are available and when they are sold out, so that the project creators can optimize their funding amount and success likelihood by strategically designing reward option menus with regard to scarcity cues and possible phantom options. Furthermore, as a consequence of our findings, reward-based crowdfunding platform operators need to evaluate whether they want to remove the often-used mechanism that campaigns display sold-out reward options. Alternatively, operators could consider to permit or even demand fundraisers to conceal sold-out rewards options or to change the original design of a reward option and thus hide or remove attributes (e.g., price and number of backers) in the phantom reward option. Thus, allowing fundraisers to cover specific attributes of the phantom options may help to avoid potential impeding effects of early birds on campaign performance.

5.6.3 Limitations and Directions for Future Research

Despite the aforementioned theoretical and practical contributions of this research, the conducted studies should be treated as an initial examination into the research field of phantom effects in reward-based crowdfunding. Therefore, we want to point out some noteworthy limitations, which at the same time also open up a series of interesting directions for future research.

First, the data collection method we employed does not fully represent the data that a real environment of a reward-based crowdfunding platform may provide. In Study 1, we recruited U.S. participants from a crowdsourcing marketplace, who not necessarily reflect backer selection behavior in an actual pledging process. We analysed the situation in which potential backers really want to acquire one of the reward options, but accepted the constrained that participants knew they would not receive the product. Additionally, we consciously omitted cultural contexts, the impact on campaigns with several funding milestones, and the possibility that potential backers have seen the reward options menu before and revisit the campaign, only to find their early bird to be sold out. Similarly, we ignore influences of the campaign description that may talk about a reward that has already become unavailable. In Study 2, on the other hand, we tried to compensate for those neglected confounds, but collected data only from one of the largest reward-based crowdfunding platforms. Consequently, to strengthen further external validity of our findings, we recommend future research to examine the phantom effect in a real setting by means of a field experiment on a online platform in different platform models, cultural contexts, and project categories.

Second, out of all possible kinds of phantom reward options, we only investigated how low priced sold-out early birds that are equivalent in content to another reward options affect the decision making. To fully comprehend the phantom effect, researchers have to conduct more studies, such as the impact of created phantom options in higher priced reward option tiers, and unearth more relations and avenues, such as the effect of the similarity of the rewards in the phantom options with the rewards in the available options (Kramer and Carroll, 2009; Huang and Zhang, 2016) and other cues in the phantom option such as so scarcity due to demand or supply (Kramer and Carroll, 2009). Starting with the category early bird offer, future studies could investigate sold-out reward options that are different from other available reward options, for instance, by providing a unique reward or a unique composition of rewards that is unavailable in other reward options. Moreover, there are also other rewards that are (naturally) limited in supply, so that these phantoms are not necessarily linked to discounts, but may still influence backers' choices.

Third, we only investigated the effect of discount amount and social proof cues in the sold-out early bird. More attributes in the sold-out reward options may be investigated, such as whether the sell-out was due to supply or demand and how tensile the sell-out is presented. Furthermore, the same investigated cues in this paper, especially the number of backers, are usually present in the other available reward options as well. Some campaigns even provide multiple early bird offers of the same reward option. These potential interaction effects might influence the phantom effect as well.

Lastly, the focus of our research was on possible shifts in the backing behavior within a specific campaign once a phantom option exists. However, the question whether the existence of a sold-out early bird affects an individual's intention to pledge in the first place is also highly relevant in this context, but could not be addressed with the data available to us. Thus, future research should further investigate the consequences of showing phantom options on a micro level (e.g., intention to pledge, backer satisfaction, and referral propensity) as well as on a macro level (e.g., effects of different designs for reward option menus on platform success).

5.6.4 Conclusion

While the success of reward-based crowdfunding platforms has been constantly growing, research has largely neglected the impact of the design of reward-option menus. Drawing on the theory of the phantom effect, we show based on the example of early bird offers how sold-out reward options can significantly influence backer's decision making in reward-based crowdfunding. We hope that our findings will encourage further studies on the effects of phantoms in crowdfunding campaigns to unearth creative and viable reward option menu designs to effectively increase the rate of successfully funded projects.

Chapter 6: Thesis Conclusion and Contributions

Decision-making in digital choice environments has become an increasingly relevant topic for IS research. This thesis contributes to the growing importance of digital nudges as well as the emerging challenges that digital choice architects need to address in order to avoid influences that unintentionally harm the decision-maker and instead nudge users towards desired outcomes. The purpose of the thesis was to shed light on the specific category of social bias and to comprehend how and why social cues function as digital nudges in various contexts. Against this backdrop, five studies in four articles have been published. The main contributions lie primarily in providing IS research a novel perspective on the nascent area of social cues in the design of digital choice environments. However, the thesis also contributes generalizable and actionable impetus for practitioners, which will be respectively discussed in the following sections.

6.1 Implications for Research and Theory

Overall, the thesis provides a broad understanding of the role of social cues as digital nudges for user decision-making in IS usage contexts. More precisely, the conducted research addressed social cues differentiated as directly-traceable social cues as well as indirectly-traceable intentional and unintentional social cues. Although all articles contribute to the originally defined research question, they focus on different social cues in different choice environments. In the following, each article's implications for research and theory are discussed in details.

6.1.1 Directly-Traceable Social Cues

Despite the current and prospective theoretical relevance of anthropomorphic IS, research on directly-traceable social cues for IS design is still in its infancy (Gnewuch et al., 2017; Seymour et al., 2018). Moreover, IS designers and researchers have experienced design challenges regarding various biases and faced setbacks in their early endeavors (Faraj et al., 2018; Jain et al., 2018; Daugherty et al., 2019). Consequently, the first two articles provide valuable insights, extending social response theory (Nass et al., 1994) as well as research on contemporary human-computer dialog and avatar design by investigating the hitherto neglected role of the directly-traceable social cues as digital nudges and their underlying mechanisms.

The first article shows that when designers employ both a verbal and nonverbal social cue in a chatbot, they can increase the adoption of a digital good by influencing the user to self-disclose personal information. Moreover, the findings reveal that the different social cues enhance one another when employed together. Thus, the findings extend previous research on social response theory primarily by demonstrating that directly-traceable social cues do not exist in a vacuum. Instead, the effectiveness of the social cues to influence and nudge user behavior depends on the user's perception of the anthropomorphic IS as a whole, so that the sum may be different from the individual effects of the social cues.

The second article examines other directly-traceable social cues, such as the visualization of an avatar as well as the articulation of a recommendation. By means of these social cues, users perceive the robo-advisor as more socially present, which in turn nudges the users to invest more money. Therefore, these findings highlight that the employment of social cues as design elements in robo-advisors can affect user decision-making to the advantage of the IS user (i.e., increasing financial well-being). Thus, the article primarily enriches previous research on social response theory and anthropomorphic IS both by investigating investment amount as a new dependent variable and by revealing that the expression of a recommendation functions as a hitherto unexplored verbal social cue.

6.1.2 Indirectly-Traceable Social Cues

There is a substantial body of research on indirectly-traceable social cues in offline and classic online context, such as e-commerce (e.g., Amazon). However, recent technological advancement and emerging digital businesses have paved the way for social cues and contexts, for which little research yet exists. Thus, the third and fourth article contribute to IS research primarily by investigating some of these evolving (e.g., seller recommendations) and new (e.g., the prominent display of sold-out products) indirectly-traceable social cues.

The third article shows that online recommendations in the form of badges and star-ratings can be used as indirectly-traceable intentional social cues in the relatively new, but steadily growing augmented commerce market to assist a user in selecting a product that better fits his or her required needs. The results strongly support the hypotheses that customers can be nudged in their product selection and purchase intention by online recommendations through a decrease in perceived product fit uncertainty. However, not all online recommendations are significantly influential: Whereas customer recommendations demonstrate to be an effective source, seller recommendations in the form of automatically-generated recommendations by intelligent recommender systems are not. Therefore, the study not only confirms previous scientific findings on the effectiveness of customer recommendations, but also extends research on online recommender systems by drawing attention to the lack of acceptance of the newly-emerging, automatically-generated seller recommendations.

The fourth article aims to investigate the potential of indirectly-traceable unintentional social cues. Therefore, it sought to advance our comprehension by investigating how previous backing behavior and the display of sold-out reward options influence decision-making of other backers in reward-based crowdfunding. Specifically, the article shows that users select an available option that is equivalent to the sold-out option with regard to reward content. This influence only exists due to the display of the social cue. Moreover, this effect can be explained by the increased desirability and urgency to buy the still available reward content. Moreover, an inverted U-shaped relationship between the amount of discount and backers' selection behaviors describes user decision-making in various continuums. More precisely, a moderate discount on the sold-out option steers significantly more backers towards the equivalent but undiscounted reward option compared to small or exaggerated discount levels. Finally, social proof - another unintentional, indirectly-traceable social cue - mitigates the relationship between the amount of discount and the phantom effect, so that a higher number of backers for the sold-out option lead to a less positive effect of the amount of discount on the backers' selection behaviors. Thus, the fourth article particularly extends research on context effects by investigating the effects of an indirectly-traceable social cue that has only recently increased in importance and frequency. Moreover, the article further contributes to research by demonstrating that social cues do not exist in a vacuum and are subject to interactions with other attributes in the choice environment regarding the adequacy and consistency of the presented information. Thus, similar to the theoretical contributions of the directly-traceable social cues, researchers need to comprehend and consider all relevant cues to identify and assess not only the cues' isolated effects but also their effects in the context of and in coexistence with other influences to effectively shape digital choice environments and alter user decision-making.

6.2 Practical Contributions

Beyond the presented theoretical contributions, this thesis also offers various pragmatic insights from an IS practitioner's point of view. In fact, the choice of social cues as the focal point of this thesis was greatly motivated by their abundant application and high relevance in IS practice. Consequently, the analysed social cues represent interesting and sometimes even counterintuitive recommendations as well as actionable and generalizable guidelines that can be easily applied to various contexts.

Practitioners as choice architects may use the findings described in this thesis to understand how and why certain social cues affect user behavior and how to nudge users to desired actions.

The results of the first and second article demonstrate that the greater the number of directly-traceable social cues, the more likely a user is to follow the guidance of a digital agent, demonstrated in the form of desired consequences, such as a higher number of newsletter sign-ups or larger investment amounts. Though this rule might not necessarily be true under all circumstances (e.g., Mori, 1970), it provides a rule of thumb specifically when not considering the employment of more complex directly-traceable social cues such as voice output or animations (e.g., McBreen and Jack, 2001; Powers et al., 2003).

The findings of the third and fourth article further show that choice architects should also consider indirectly-traceable social cues as potential nudges. Already established cues, such as customer recommendations, social proof and sold-out options, seem to be easily applicable in newer contexts, such as augmented commerce and reward-based crowdfunding. Consequently, choice architects can apply these cues, for example, to increase crowdfunding success. However, the results of the third article indicate that choice architects face the challenge that unprecedented nudges, such as automatically generated recommendations by recommender systems, must be designed in a way that users accept them. Similarly, as revealed in the fourth article, the already established nudges, such as cues with regard to social proof and discounts, do not exist in a vacuum. Consequently, choice architects need to be aware of which characteristics their employed cues possess as well as consider the combination and arrangement in which these cues work best.

6.3 Limitations and Directions for Future Research

Despite the aforementioned theoretical and practical contributions of this research, the emerging thesis should be treated as an initial examination into the research field of social cues as digital nudges in IS usage contexts. Therefore, I want to point out some noteworthy limitations, which at the same time also open up a series of interesting directions for future research.

First, the studies incorporated in this thesis may suffer from methodological limitations, and thus require further evidence to improve internal or external validity. For example, some controlled laboratory experiments checked user behavior at a single point of time under supervised conditions, thus exerting high internal validity but neglecting external validity. Future research may complement and support these initial findings, such as a longitudinal field study.

Second, since the investigated research question addresses several forms of social cues in IS, this dissertation intends to showcase the importance of social cues in numerous applications and is, therefore, to be understood as a glimpse of research into various contemporary IS usage contexts, including crowdfunding, augmented commerce and robo-advisory. More social cues, IS contexts, and decisions exist that may be worthwhile examining in the future, not to mention social cues and related circumstances that are yet to emerge.

Third and lastly, the thesis addresses predominantly the IS usage context. Consequently, future research may examine the generalizability of the thesis's findings for other IS contexts.

6.4 Conclusion

To the best of my knowledge, this thesis provides the first sustained attempt to research social cues as digital nudges and their impact on user behavior in IS usage contexts. Overall, it is an initial step towards understanding the interplay between the design of IS artefacts with social cues and users' biased decision-making processes. Therefore, this thesis extends prior IS research on the role of human factors in the IS discipline. Moreover, the preliminary findings not only reveal potential social cues in various contemporary IS usage contexts with their individual and unique environmental circumstances, but also pave the way for even more explorations. I hope that my results will embolden future studies to further advance the comprehension of the role of the myriad social cues in IS to advance humanistic outcomes as well as to encourage practitioners to embrace social cues in their designs of IS.

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Eidesstattliche Erklärung

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Die Arbeit wurde bisher nicht zu Prüfungszwecken verwendet und noch nicht veröffentlicht.

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