INDIVIDUALIZED CHOICES AND DIGITAL NUDGING: MULTIPLE STUDIES IN DIGITAL RETAIL CHANNELS

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Table of Contents

Tables

Figures

List of Abbreviations

ANOVA	Analysis of Variance
AVE	Average Variance Extracted
BFI	Big Five Inventory
BIT	Behavioral Intervention Team
BSRI	Bem Sex Role Inventory
Cb. α	Cronbach's Alpha
CB-SEM	Covariance-Based Structural Equation Modelling
CR	Composite Reliability
DINU	Digital Nudging Process Model
DSR	Design Science Research
DSS	Decision Support System
EU	European Union
EUR	Euro
GDPR	General Data Protection Regulation
H	Hypothesis
HCI	Human-Computer-Interaction
IQR	Interquartile Range
IS	Information Systems
IT	Information Technology
MA	Meta-Analysis
MC	Multi-Channel
MCMD	Multichannel Customer Management Decision
No.	Number

PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modelling
QA	Quantitative Analysis
RQ	Research Question
RCT	Randomized Controlled Trials
SD	Standard Deviation
SDG	Sustainable Development Goal
SEM	Structural Equation Modelling
SLR	Systematic Literature Review
S-O-R	Stimulus-Organism-Response
TAM	Technology Acceptance Model
UI	User Interface
UN	United Nations
VIF	Variance Inflation Factor

Summary

Information technology has led to the development of new digital retail channels (Avalaunch Media 2009; Watson et al. 2015). This has dramatically increased consumers' options to purchase products and services in different channels, enabling a multi-channel behavior of consumers (Verhoef et al. 2007). With many advantages, the development also bears negative consequences for consumers, e.g. by a prolonged purchasing process or by competing information and experiences in different channels (Brynjolfsson et al. 2013; Rawson et al. 2013). In turn, providers suffer from cross-channel free-riding behavior of consumers (Chiu et al. 2011; Chou et al. 2016) or the choice of those channels with higher transaction costs (PwC 2012).

The negative consequences can, in part, be balanced with an individualized user interface (UI) which can be more effective than a standard interface for the whole population (Nov, Arazy, López, et al. 2013). UIs can be individualized on the basis of consumer characteristics (e.g. Nov, Arazy, Lotts, et al. 2013; Oulasvirta and Blom 2008). Among such characteristics, particularly the personality of consumers is applicable (Codish and Ravid 2014; Nov, Arazy, López, et al. 2013). Yet, current research lacks the knowledge of how channel characteristics interact with individual consumer characteristics. Once the interaction is known, it can be used to guide, or to "nudge" (Thaler and Sunstein 2008) consumer behavior. Hence, we assume that the knowledge of such interaction effects can also be used to individualize tools of choice architecture (Strahilevitz and Porat 2014; Thaler and Sunstein 2008). Based on this assumption, we aim to understand consumer behavior, and how to nudge it through the interplay between channel characteristics and individual consumer characteristics in digital retail channels.

The first study addresses determinants of multi-channel behavior by means of a systematic literature review (Webster and Watson 2002) as we identified the need to integrate knowledge from a wide range of disciplines. Based on 53 studies we develop a morphological box and cluster multitudinous characteristics and outcomes into four dimensions: channel, context, consumer and product. Through a numerical counting approach, we highlight under-researched areas, and derive three important research questions (RQs) for future exploration.

Based on the findings of the first study, the second study investigates the link between individual characteristics, especially personality traits and gender roles, and channel characteristics. This link is particularly helpful for the individualization of digital retail channels. A laboratory experiment with 236 participants is conducted and the resulting data is analyzed using structural equation modelling (Hair et al. 1998). Thereby, we are able to extend an existing decision-making model (Kim et al. 2008) with personality traits and gender roles. For example, we can show that agreeableness is positively related to trust, and that neuroticism has a strong negative relationship with perceived benefits. This knowledge can be used to influence consumer behavior.

When turning to influencing consumer behavior, we use the concept of nudging (Thaler and Sunstein 2008). Thus, the third study particularly aims to clarify how nudges can be classified. It also determines the influencing factors for the effect sizes of different categories of nudges in previous studies. Therefore, we conduct a quantitative literature review with 100 primary studies from different disciplines and derive another morphological box with eight dimensions to classify nudging studies. We estimate that the nudges have a median effect size of 21% and that only 63% of all nudging treatments produce significant results. Moreover, we find that the type of nudge as well as the context have an influence on the effect size of the treatment. The results contribute to a nuanced view on nudging and provide avenues for future research for researchers as well as implications for practitioners.

The third study has taught us that nudge treatments are often insignificant. Digital environments offer the chance to individualize digital nudges according to the individual consumer characteristics, such as their personality. To test for this interaction in the fourth study, we design and conduct an online survey experiment with 452 participants implementing three different digital nudges (defaults, social norms, warnings) in a sustainable consumption context. The results are surprising: While defaults are effective in increasing the choice of sustainable products, social norms reduce this choice. Further, we show that the interaction of certain digital nudges and personality traits can enhance or diminish the effectiveness of the digital nudge. This sheds light on digital nudging and shows that digital nudges can have positive as well as negative effects, depending on the type and the recipient of it.

The contributions of the thesis are multifold. Overall, we enhance the understanding of consumer behavior in digital retail channels by providing opportunities and insights on the limits of influencing it. In particular, we conceptualize determinants of multi-channel behavior and offer avenues for future research. Following these avenues, we extend a prominent decision-making model (Kim et al. 2008), and show how personality traits and gender roles antecede channel characteristics. Moreover, based on a quantitative literature review, we develop a morphological box of empirical nudging studies and extend the knowledge of the (in)effectiveness of nudging. In addition, we shed light on the moderating effects of personality traits in digital nudging.

Practitioners can use the findings from this work to adapt their digital retail channels to the individual consumer characteristics. To do so, designers of digital retail channels can use today’s technological advancements of deriving personality traits based on social media data (Bachrach et al. 2012; Markovikj et al. 2013) and adapt their channels by adding certain channel characteristics (Study 2) or digital nudges (Study 4). Moreover, policy makers can implement the findings to increase the impact of environmentally friendly policies, for example by wording social norms to promote sustainable behavior online exactly and cautiously.

1 Introduction

1.1 Motivation

New technologies are at the center of humankind's innovation efforts. Among others, they have led to the development of new retail channels (Avalaunch Media 2009; Watson et al. 2015) which gives consumers unprecedented access to products and services independent of time and location. This access has created a new type of consumer behavior across different channels. Before the age of online and mobile channels, consumers frequented stores and branches while nowadays they are able to combine several channels within one purchasing process (Gensler et al. 2012; Neslin and Shankar 2009; Verhoef et al. 2007). The terms online channel or Internet refer here to the traditional desktop-based access possibilities and, together with other channels relying on modern communication technologies, can be subsumed under the term "digital retail channels" (Bianchi et al. 2016) (hereafter referred to as "digital channels").

This multi-channel behavior has several implications for consumers and providers. On the one hand, providers can increase sales and profits through better access to their channels, and operating multiple channels generally benefits the firm (Kumar and Venkatesan 2005; Neslin and Shankar 2009). On the other hand, consumers can choose those channels with higher transaction costs for providers by visiting the branch instead of using digital channels (PwC 2012). Moreover, they can engage in cross-channel free-riding behavior (Chiu et al. 2011; Chou et al. 2016) which could outweigh the benefits of additional sales. Similarly, consumers now profit from an increased variety, higher flexibility and convenience in their shopping behavior (e.g. Farag et al. 2006; Gensler et al. 2012). Yet, consumers could suffer from a prolonged purchasing process or from competing information and experiences in different channels (Brynjolfsson et al. 2013; Rawson et al. 2013). Moreover, many consumers still associate high risks with and demonstrate little trust in digital channels (Chou et al. 2016; Dinev and Hart 2006; Everard and Galletta 2006). As a consequence, only few consumers rely exclusively on digital channels (Sopadjieva et al. 2017). Overall, we conclude that consumers and providers do not profit from technological innovation as much as they could.

One possible solution to this dilemma is individualizing the design of digital channels. Especially by implementing an individualized user interface, which can be more effective than a standard interface for the whole population (Nov, Arazy, López, et al. 2013), the negative consequences can be balanced. Previous studies have shown that individualizing the UI according to the individual user or consumer characteristics increases user's online contribution (Nov, Arazy, López, et al. 2013) or participation (Nov, Arazy, Lotts, et al. 2013). Moreover, a well-designed individualization might increase the use of new technology (Oulasvirta and Blom 2008), and it has proven to be effective in other areas of information systems (IS), e.g. in gamification (Codish and Ravid 2014) or nudging based on big data

(Strahilevitz and Porat 2014; Thaler and Sunstein 2008). Hence, similar advantages and outcomes are also expected for the domain of digital channels (Walsh and Godfrey 2000). Yet, few consumers want to customize or individualize the UI themselves so that it is the responsibility of the providers to integrate an automated individualization. However, researchers and practitioners lack the knowledge of how channel characteristics interact with individual characteristics. In particular, UIs can be individualized based on the personality of consumers (Codish and Ravid 2014; Nov, Arazy, López, et al. 2013).

Personality traits can be described as "an individual's dispositions or tendencies that lead to certain attitudinal and behavioral patterns across situations" (Junglas et al. 2008, p. 391; McCrae and Costa 1987). In other words, personality traits predefine to some extent patterns of how we act in different situations. They are particularly applicable to the individualization of user interfaces as they have proven to be meaningful moderators in a variety of studies in digital environments (Bansal et al. 2010; Liu et al. 2013; Nov, Arazy, López, et al. 2013; Rodríguez-Torrico et al. 2017). Personality traits can be measured with established inventories, such as the Big Five Inventory (BFI) (McCrae and Costa 1987; McCrae and John 1992) (see Chapter 2.3.1)

The interplay between digital channels ("IT Artifact") and individual characteristics ("Individuals") is also reflected in the identity of IS research (Sidorova et al. 2008) which is depicted in Figure 1. The dimension of IT and individuals is one integral part of the IS Research Identity and it is comprised of four sub-dimensions, namely impact, usage, capabilities, and practices (Sidorova et al. 2008). These sub-dimensions examine primarily psychological aspects of human-computer interactions (HCI) and focus for instance on individual technology acceptance, online consumers or personalization and privacy (Sidorova et al. 2008). Hence, it fits perfectly with the challenges describe above as well as the theoretical and conceptual foundations in Chapter 2.

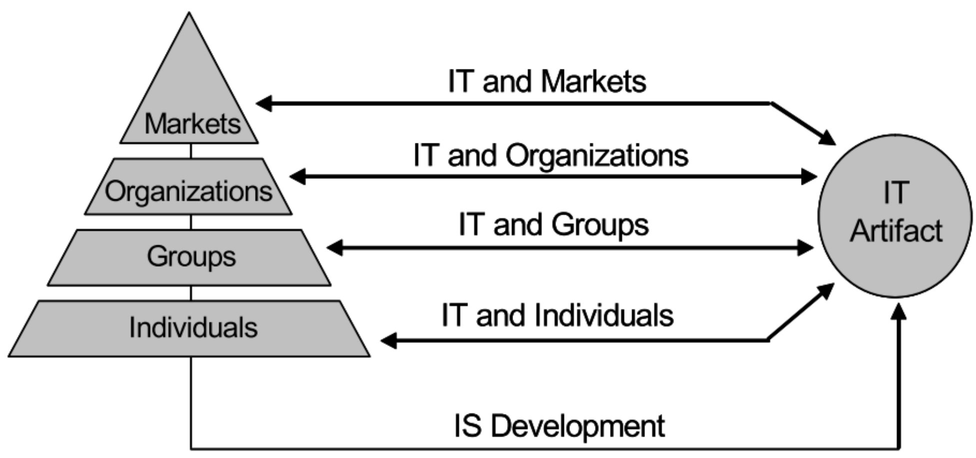

Figure 1. Model of IS research identity based on Sidorova et al. (2008)

Once the interaction of IT and individuals is known, it can be used to guide, or "nudge" (Thaler and Sunstein 2008), consumer choices using individualized digital nudges. Individualization of nudges has been suggested by various studies in different settings (e.g. Goldstein et al. 2008; Halpern 2016; Johnson et al. 2012), but is a concept that has not been verified empirically. Individualization of nudges is difficult in conventional settings but more promising where digital environments are concerned ("digital nudging"), which becomes increasingly important due to the development of new channels.

Therefore, this thesis aims to understand the interplay between channel characteristics and individual consumer characteristics in digital channels to individualize channel choices and nudge consumer choices. The challenges and strategies of understanding and influencing consumer behavior are translated into research questions (RQs) in the following section.

1.2 Research Questions

The rise of new technologies and the combination of different channels by consumers raise the question which channel is considered under which circumstances. Only few studies have collected determinants of multi-channel (MC) behavior (Mirsch et al. 2016a; Neslin et al. 2006; Trenz and Veit 2015; Zhang and Benyoucef 2016). All of these studies have some drawbacks, mostly because they do not derive the clusters of determinants methodologically, because they focus on the provider perspective (Mirsch et al. 2016a), or because they do not use a systematic literature review (SLR) (Trenz and Veit 2015). Moreover, multi-channel behavior in the context of physical products is widely researched (e.g. Inman et al. 2004; Keen et al. 2004; Thomas and Sullivan 2005), but not all results are transferrable to services. This leads to the following research question:

RQ 1: *What are determinants of multi-channel behavior for products and services?*

Research question 1 is addressed by a systematic literature review in Study 1.

Once the determinants of multi-channel behavior are conceptualized, the next step is to look at the linkage between individual characteristics, especially personality traits and gender roles, and channel characteristics. Only few consumers rely exclusively on digital channels and most combine offline and online channels during the purchasing process (Sopadjieva et al. 2017). This bears negative consequences for providers (Chou et al. 2016; PwC 2012) and consumers (Brynjolfsson et al. 2013; Rawson et al. 2013). One possibility to curb such consequences might be an individualization of digital channels according to the individual consumer characteristics. Yet, to be able to design and to individualize digital channels requires an understanding of the interplay between individual and channel characteristics. To do so, we build upon an existing decision-making model (Kim et al. 2008). Hence, we address the following research question:

RQ 2: *What is the effect of personality traits and gender roles on perceived risk, trust, and perceived benefits?*

To answer research question 2, we conducted a laboratory experiment in a mid-sized German city with 236 participants.

Research questions 3 and 4 are dedicated to individualized nudging (Thaler and Sunstein 2008) of consumer choices. Since the origin of the nudging concept in 2008, governments in the United Kingdom (UK), Germany and other countries have implemented departments of behavioral economics (e.g. Behavioral Insights Team 2016; Social and Behavioral Sciences Team 2016). Therefore, nudges now affect citizens through their influence on the political decision-making process, but it remains unclear if nudges really work and, if so, under which conditions. For example, the Science and Technology Committee of the UK, overseeing the Behavioral Intervention Team (BIT), has raised doubts whether experiments can be supported by appropriate evidence (see Halpern 2016; Kosters and Van der Heijden 2015). In addition, recent studies indicate limited effects of nudging (D'Adda et al. 2017; Esposito et al. 2017), or even report backfire effects with unintended consequences (e.g. Liu et al. 2016; See et al. 2013). Moreover, one of the authors of the nudging concept has even dedicated a separate journal paper on "nudges that fail" (Sunstein 2017). Consequently, we address the following research question:

RQ 3: *How can nudges be classified and what are the influencing factors for the effect sizes of different categories of nudges?*

Research question 3 is addressed by a SLR (vom Brocke et al. 2009) and a quantitative analysis (QA) (Kitchenham 2004; Pickering and Byrne 2014; Stanley 2001).

Finally, the preceding findings are translated into a veritable real-world problem, that is the lack of sustainability which is one of the key challenges of our time (United Nations 2018). While many consumers wish to contribute to a more sustainable world, they often fail to behave as intended, which is labelled "attitude-behavior gap" (Ajzen 2001; Vermeir and Verbeke 2006). Digital tools of choice architecture, so-called digital nudges (Schneider et al. 2018; Thaler and Sunstein 2008), could help to overcome this gap. Based on the quantitative literature review (Study 3), especially defaults, social norms and warnings were identified as promising digital nudges. Moreover, it is reasonable to assume that individualizing the digital nudge according to the individual characteristics of the decision-maker improves the effectiveness of the digital nudge. While this relationship was proposed theoretically (Goldstein et al. 2008; Halpern 2016; Johnson et al. 2012), it has not yet been verified empirically. Personality traits are suitable individual characteristic as they have proven to be differentiating in earlier IS studies (Bansal et al. 2010; Svendsen et al. 2013). Hence, we aim to address the following research question:

> **RQ 4**: *How do different types of digital nudges (defaults, social norms and warnings) influence the choice of sustainable products in digital channels under consideration of personality traits?*

Research question 4 is addressed by an online survey experiment with 452 participants. The data is analyzed using a logistic regression model.

1.3 Thesis Structure

This thesis is structured as follows (see Figure 2).

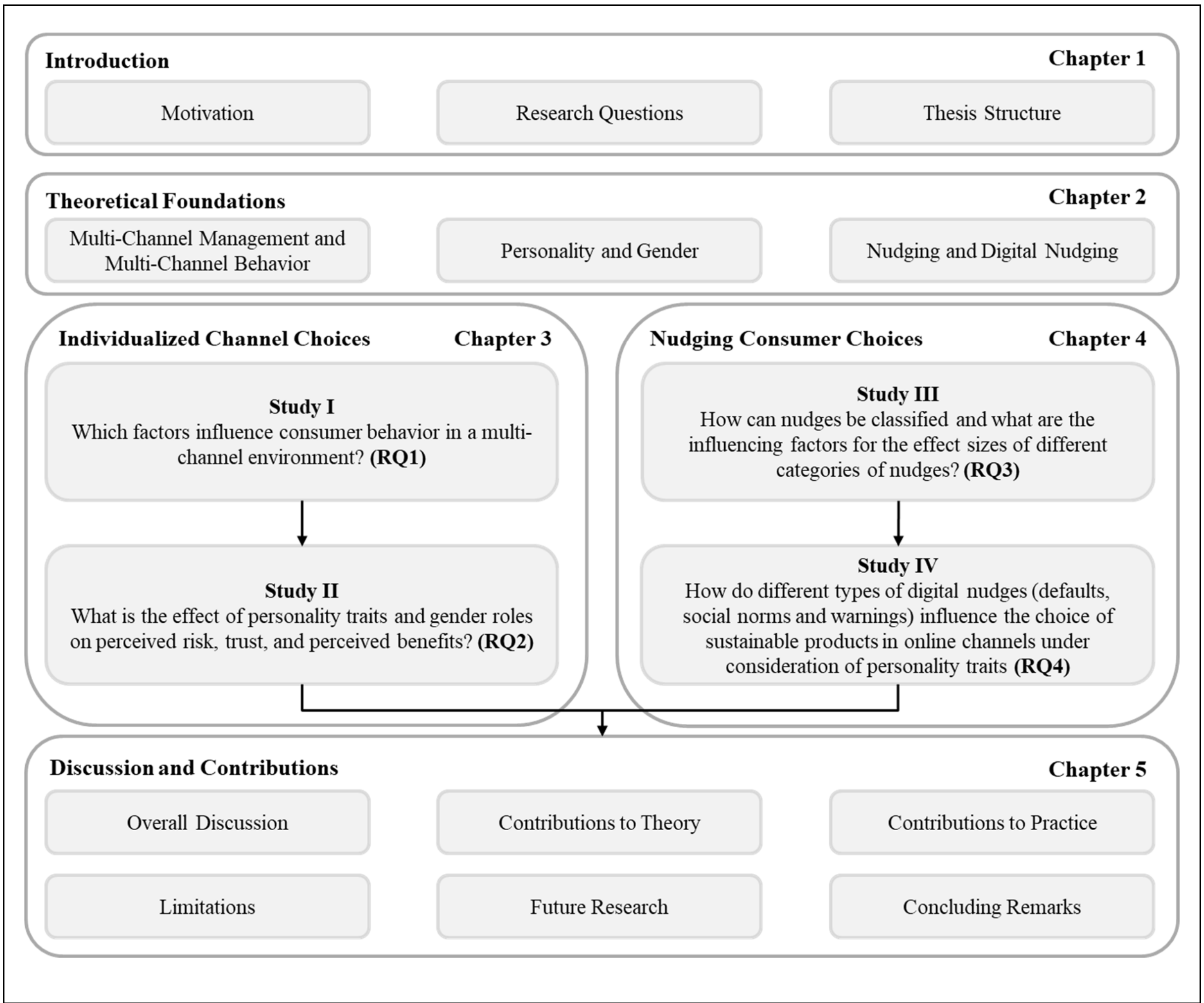

Figure 2. Structure of the thesis

Firstly, the theoretical and conceptual foundations are derived and defined which we draw on throughout this doctoral thesis. Thereby, we outline different multi-channel frameworks and highlight the consumer and the provider perspective. In addition, we present theories for individual characteristics as well as their respective inventories, such as the Big Five Inventory (McCrae and Costa 1987; McCrae and John 1992) and the Bem Sex Role Inventory (Bem 1974). The chapter is concluded by a section on behavioral economics and nudging. Secondly, Chapter 3 contains two studies that shed light on individualized channel choices. Study 1 analyzes determinants of multi-channel behavior by means of a systematic literature review while Study 2 outlines a laboratory experiment that is designed to research the relationship of personality traits and channel characteristics. Thirdly, Chapter 4 (comprised of Study 3 and Study 4) is dedicated to research the possibilities of nudging consumer choices in digital channels. Study 3 encompasses a quantitative literature review on the concept of (digital) nudging whereas Study 4 tests different digital nudges against each other to increase sustainable product choices. Finally, the thesis concludes with a discussion including limitations and areas of future research (Chapter 5).

This thesis is the synopsis of extensive research conducted throughout the past years. Parts of this dissertation have already been published at international peer-reviewed conferences or are under review in leading peer-reviewed journals of information systems and economics. Thus, this thesis provides the institutional framework of the respective research activities and publications. Specifically, this dissertation is based upon the following papers (Hummel et al. 2016; Hummel, Vogel, and Maedche 2018; Hummel, Vogel, Schacht, et al. 2018; Hummel and Maedche 2018):

1. Hummel, D., Schacht, S. and Maedche, A. (2016). Determinants of Multi-Channel Behavior: Exploring Avenues for Future Research in the Services Industry. In: *Proceedings of the 37th International Conference on Information Systems (ICIS)*, 1–12.
2. Hummel, D., Vogel, T., Schacht, S. and Maedche, A. (2018). From the Why to the Who in Channel Choices: The Role of Personality Traits and Gender Roles to Individualize Digital Channels. *Under review in European Journal of Information Systems*, 1–24.
3. Hummel, D. and Maedche, A. (2018). How Effective Is Nudging? A Quantitative Literature Review on the Effect Sizes and Limits of Empirical Nudging Studies. *Under review in Journal of Behavioral and Experimental Economics*, 1–29.
4. Hummel, D., Vogel, T. and Maedche, A. (2018). Individualized Digital Nudges for Sustainable Product Choices in Digital Retail Channels: The Moderating Role of Personality Traits. *Working Paper*, 1–32.

A full list of the author's publications can be found in the Appendix.

2 Theoretical and Conceptual Foundations

This thesis relies on theoretical and conceptual foundations from marketing, psychology and information systems. Therefore, Chapter 2 outlines the research streams (Chapter 2.1), the frameworks of multi-channel management and multi-channel behavior (Chapter 2.2), the individual characteristics of personality and gender roles (Chapter 2.3), behavioral economics and (digital) nudging (Chapter 2.4), as well as an overview of which theoretical and conceptual foundations are employed in the respective studies (Chapter 2.5).

2.1 Research Streams

Figure 3 provides an overview of the relevant research streams and exemplary papers within each stream. Thereby, the research stream on channel choices can be split into a marketing-oriented direction (focusing on multi- and omni-channel issues) and an IS-oriented direction (focusing on digital channel usage). The individual characteristics, labelled as "Personality, gender and IS", represent the second research stream with a focus on personality traits and gender roles in IS studies. Finally, nudging, a sub-discipline of behavioral economics, is presented as the third research stream (e.g. Ayres et al. 2013; Bond et al. 2012; Thaler and Sunstein 2008). The research gaps, which were outlined in the introduction, are illustrated in the respective research streams or at their intersections.

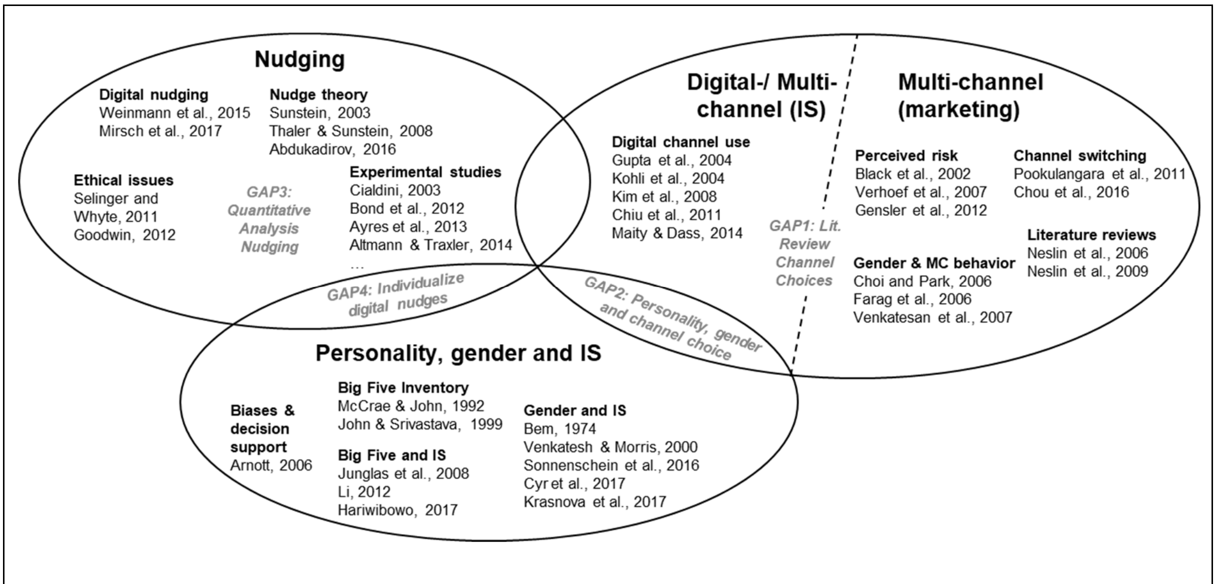

Figure 3. Overview of research streams, theoretical foundations and research gaps

In the following, we outline the relevant frameworks and theories within each research stream.

2.2 Frameworks of Multi-Channel Management and Multi-Channel Behavior

Consumer behavior nowadays occurs in a multi- or omni-channel setting (Verhoef et al. 2007, 2015). Most studies can be divided along the lines of demand and supply, or a provider perspective and a consumer perspective (e.g. Neslin et al. 2006). While the provider perspective focuses on the implementation and management of multiple channels, the consumer perspective analyzes the motives, behaviors and characteristics of multi-channel consumers.

2.2.1 Provider Perspective

The provider perspective of multiple channels evolves around the management of a system of sales and distribution channels. Therefore, *multi-channel customer management* is "the design, deployment, coordination, and evaluation of channels through which firms and customers interact, with the goal of enhancing customer value through effective customer acquisition, retention, and development" (Neslin et al. 2006, p. 95). It is thus the management of a multi-channel system from the perspective of a provider.

Building on this definition, Neslin and Shankar (2009) present a multichannel customer management decision (MCMD) framework based on five steps: Analyze Customers, Develop Multichannel Strategy, Design Channels, Implement, Evaluate (see Figure 4).

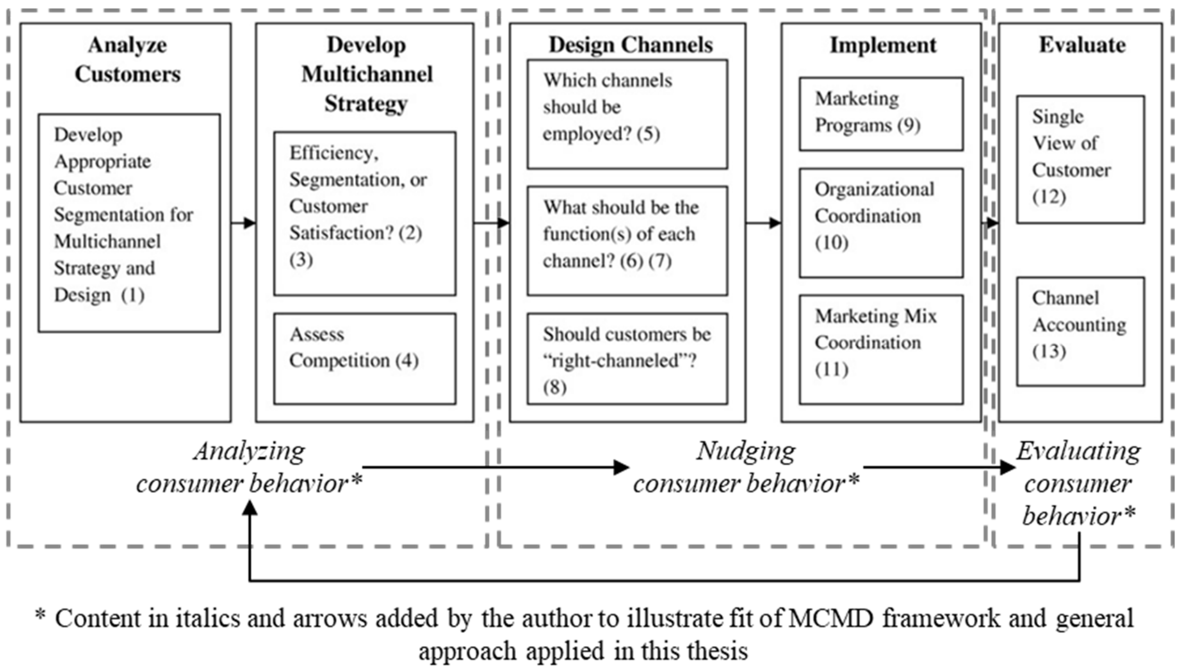

Figure 4. MCMD framework based on Neslin and Shankar (2009)

Neslin and Shankar (2009) present research questions for each phase of the MCMD framework. They conclude that prior research has developed a good understanding of some issues (e.g. the value of a multi-channel vs. single-channel consumers) while other issues remain (Neslin and Shankar 2009). For the remaining issues, they formulated avenues for future research. The framework can be matched to the structure of this thesis by analyzing and nudging (and finally evaluating) consumer behavior.

Historically, the provider perspective has dealt with question of whether multiple channels are more profitable than single channels (Bilgicer et al. 2015; Cambra-Fierro et al. 2016; Kushwaha and Shankar 2013), or how the elimination of channels affects purchase incidence, order size and channel choice (Konuş et al. 2014). Nowadays, as most companies operate multiple channels (Brynjolfsson et al. 2013; Verhoef et al. 2015), the research focuses on the interplay between the different channels which has led to the development of the term *omni-channel management* in 2015.

The concept of omni-channel management is defined as "the synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over channels is optimized" (Verhoef et al. 2015, p. 176). Other researchers have picked up the concept to explain technology acceptance and use (Juaneda-Ayensa et al. 2016), to reflect on the strategic implications (Chopra 2016; Hosseini et al. 2018), or to refine the concept of omni-channel management (Mirsch et al. 2016b, 2016a; Saghiri et al. 2017).

In contrast to the provider perspective, this thesis focuses predominantly on the consumer perspective of multi-channel behavior.

2.2.2 Consumer Perspective

Terminology of consumer perspective

To begin, we aim to clarify the terminology of the consumer perspective. *Consumer behavior* is the overarching term used in this thesis. It describes "the behavior of the consumer or decision maker in the market place of products and services. It often is used to describe the interdisciplinary field of scientific study that attempts to understand and describe such behavior" (American Marketing Association 2018). The definition confirms the research objectives stated in the introduction to understand (and influence) consumer behavior. Consumer behavior can be divided into various sub-dimensions such as cross-buying, purchase frequency, share of wallet allocations, channel migration, and channel choices (Sullivan and Thomas 2004). Unlike Sullivan and Thomas (2004), we see channel choices as a sub-dimension of consumer choices. Among such *consumer choices*, consumers can choose between products, channels and others. Thereby, *channel choice* refers to "the decision to frequent one of the distribution channels offered by the same retailer" (Sullivan and Thomas 2004, p. 3). In turn, multi-channel choice has no universally accepted definition. Hence, we refer to it as "the decision to frequent multiple distribution channels offered by one or more retailers across the different stages of the purchasing process" (own definition). However, the terms *multi-channel choice* and *multi-channel behavior* are often used interchangeably (e.g. Oppewal et al. 2013; Sonderegger-Wakolbinger and Stummer 2015) or are combined to *multi-channel choice behavior* (Al-Majali and Prigmore 2010; Choi and Park 2006) in most publications. Therefore, similar to most researchers, multi-channel behavior and (multi-)channel choice will be used synonymously in this thesis.

The *purchasing process* consists of the five stages of problem recognition, search, evaluation, purchase, and after-sales (Gupta et al. 2004), but for reasons of simplicity, we assume that it consists of a pre-purchase stage, a purchase stage as well as a post-purchase stage (see also Chapter 3.1). Finally, multi-channel behavior occurs when different *retail channels* (hereafter just "channels") are combined within one purchasing process. Traditionally, consumers had to choose among various offline channels such as the branch or the catalog. With the rise of new technologies, they were also able to choose digital retail channels (hereafter referred to as "digital channels"). Digital channels encompass all channels which rely on modern communication technologies such as the online or mobile channel.

Theoretical and conceptual foundations of multi-channel behavior

The consumer perspective is concerned with consumer behavior in multiple channels, but also the characteristics of multi-channel consumers (e.g. Konus et al. 2008; McGoldrick and Collins 2007). For example, Konus et al. (2008) identify three segments (uninvolved shoppers, multi-channel enthusiasts and store-focused consumers), while McGoldrick and Collins (2007) segment consumers by the respective channel usage (store-prone, catalogue-prone, Internet-prone and multi-channel shoppers).

In the consumer perspective, no leading model prevails, but many different approaches with diverging constructs study the multi-channel behavior of consumers (Chou et al. 2016; Fang et al. 2006; Gensler et al. 2012; Graupner and Maedche 2015; Gupta et al. 2004; Herhausen et al. 2015; De Keyser et al. 2015; Kim et al. 2008; McKnight et al. 2017; Schoenbachler and Gordon 2002). Each one focuses on different aspects, but it is worthwhile to exemplarily highlight the model of Kim et al. (2008).

It is based on a theoretical framework of consumer trust, perceived risk, perceived benefits, and intention of purchase (see dark-colored constructs in Figure 5 below). Thereby, *perceived risk* is defined as "a consumer's belief about the potential uncertain negative outcomes from the online transaction" (Kim et al. 2008, p. 546), *perceived benefits* as "a consumer's belief about the extent to which he or she will become better off from the online transaction with a certain Website" (Kim et al. 2008, p. 547) and *trust* as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al. 1995, p. 712). These constructs are part of many channel choice models (e.g. Black et al. 2002; Lamberti et al. 2014; Verhoef et al. 2007) and date back to marketing theories from the 1970s (e.g. Peter and Tarpey 1975; Wilkie and Pessemier 1973), such as the valence concept (Peter and Tarpey 1975). Subsequently, this basic theoretical framework is expanded with experienced-based, cognition- based, affect-based and personality-oriented constructs (Kim et al. 2008). These constructs serve, among others, as foundations for Study 1 and Study 2.

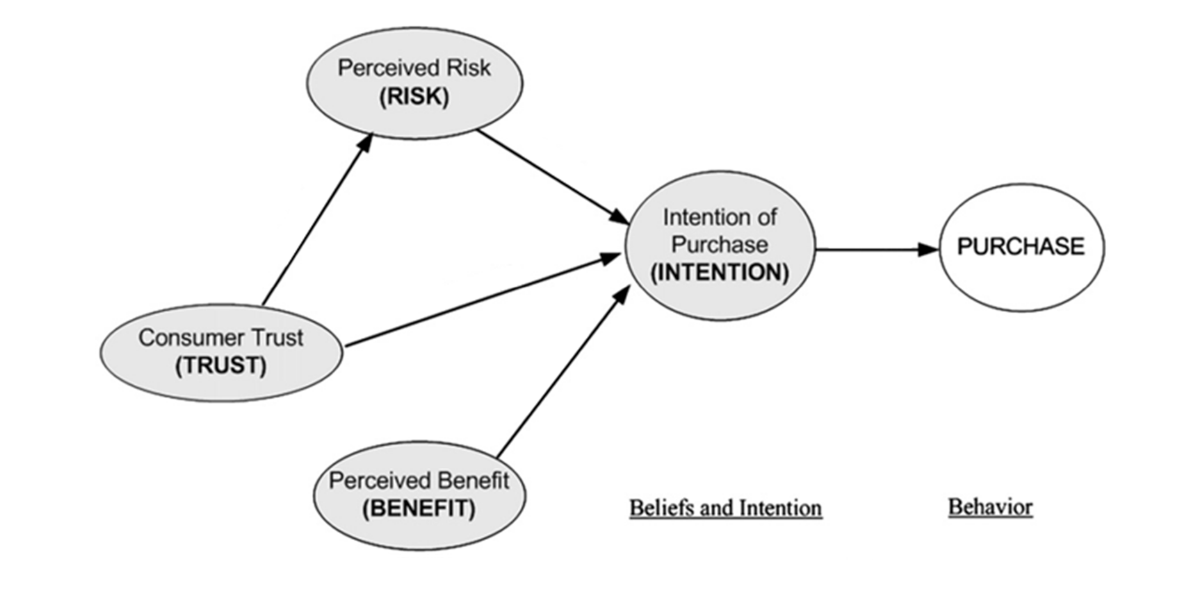

Figure 5. Exemplary model of channel choices based on Kim et al. (2008)

When aiming to understand consumer behavior, it is critical to highlight individual consumer characteristics (see e.g. Konus et al. 2008; Schoenbachler and Gordon 2002; Turkyilmaz et al. 2015; Wang et al. 2006). In particular, we focus on personality traits and gender roles of consumers.

2.3 Individual Characteristics

2.3.1 Personality

Personality theories

Many theories in psychology and medicine can be explained through the interplay between biology, psychology and sociology, often labelled the "biopsychosocial model" (Engel 1977). Within psychology, models of personality have occurred in three waves, the psychodynamic model (mainly based on Sigmund Freud), the behavioristic model (mainly based on Iwan Pawlow and classical conditioning), and the interactionist model (Stemmler et al. 2011; Vogel and Wänke 2016). Thereby, interactionism relates to the interaction of individual, person-specific conditions with situation-specific stimuli to explain behavior (Hammond 1966; Reynolds et al. 2010; Stemmler et al. 2011; Tett and Burnett 2003). Nowadays, the latter model is regarded as the most influential one, and our research is based on the behavioristic approach.

Given the various approaches, different definitions of personality traits exist (Roberts 2009). For example, Allport (1961) describes personality traits as a “neuropsychic structure having the capacity to render many stimuli functionally equivalent, and to initiate and guide equivalent (meaningfully consistent) forms of adaptive and expressive behavior” (Allport 1961, p. 347). Other researchers define personality traits as “an individual’s dispositions or tendencies that lead to certain attitudinal and behavioral patterns across situations” (Junglas et al. 2008, p. 391; McCrae and Costa 1987). A common denominator of all definitions is the finding that personality traits are stable characteristics that allow to understand, explain and predict the behavior of individuals (Stemmler et al. 2011). In other words, the definitions assume behavioral patterns and thus a certain stability across situations. Personality traits are formed at younger ages, remain somewhat stable in the following years, and are only subject to change again at older ages (Specht et al. 2011). Other researchers argue that personality traits remain stable across the entire lifespan (Junglas et al. 2008; McCrae and Costa 1991).

Various models exist to differentiate personality traits from other variables such as attitudes, states or behavior (Stemmler et al. 2011). Thereby, attitude “refers to the degree to which a person has a favorable or unfavorable evaluation or appraisal” of a construct, e.g. a behavior in question (Ajzen 1991, p. 188). Attitudes include components of states (Vogel and Wänke 2016) which are behavioral differences of an individual dependent on the situation or time (Stemmler et al. 2011). By definition, states are not stable, but dependent on the situation (Vogel and Wänke 2016). Moreover, personality traits have to be distinguished from skills (e.g. intelligence) which are as stable as personality and also vary between individuals (Vogel and Wänke 2016). Skills predict achievements and performance but, unlike personality traits, they do not reveal anything about social interactions, for example whether an individual is friendly or aggressive.

We exemplarily highlight the sociogenomic model of personality traits of Roberts and Jackson (2009) which is illustrated in Figure 6. The model reflects the biopsychosocial model (Engel 1977) by being based on biological factors (biology), traits (psychology) and environmental factors (sociology). In particular, it assumes that personality traits are based on biological factors and states. Biological factors are genetically inherited and can be for example a range of hereditary temperamental starting values (Roberts 2009). In turn, traits can also influence biological factors and states. States are formed by thoughts, behaviors and feelings (Roberts 2009; Roberts and Jackson 2009). Finally, the environment influences both states and biological factors, for example by shaping the temperamental starting values through environmental experiences (Roberts 2009; Roberts and Jackson 2009). The model can, for instance, be applied to personality trait development (Roberts 2009).

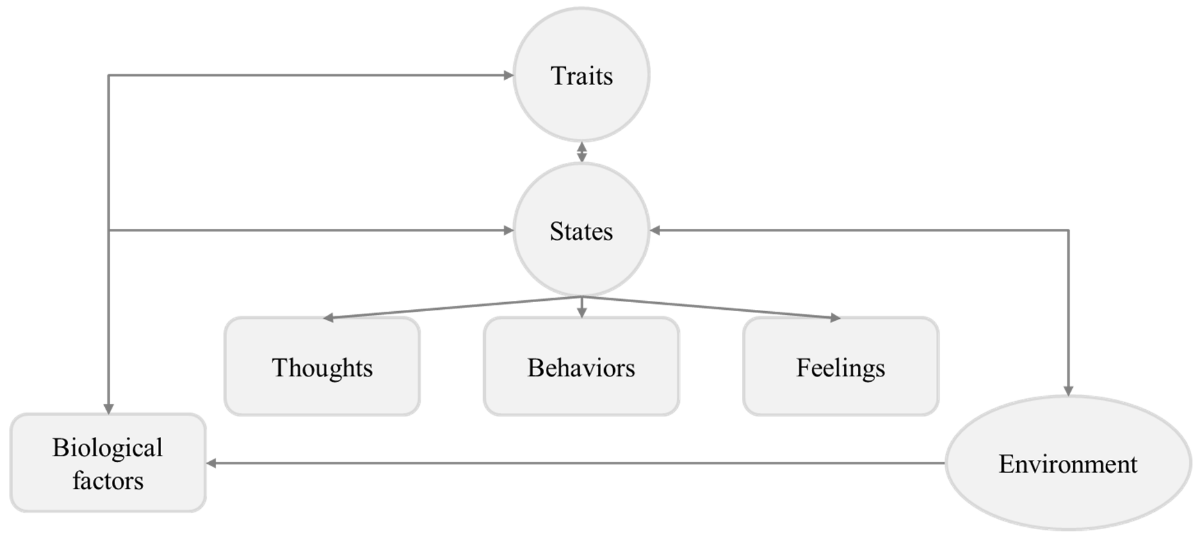

Figure 6. Sociogenomic model of personality traits based on Roberts (2009)

To measure personality traits, this thesis relies on the established Big Five Inventory (McCrae et al. 2005; McCrae and Costa 1987; McCrae and John 1992).

Big Five Inventory

Several inventories exist to summarize personality traits, such as the Big Five Inventory (McCrae and Costa 1987; McCrae and John 1992), the Five-Factor Personality Inventory (Hendriks et al. 1999), their respective updated versions (e.g. McCrae et al. 2005), or, less academic but popular among practitioners, the Myers–Briggs Type Indicator (Jahng et al. 2002; Myers-Briggs 1962). This thesis relies on the prominent Big Five Inventory as it is the most researched and most cited inventory of personality traits. Moreover, the BFI has proven to be predictive for a variety of variables, for example life satisfaction (Rammstedt 2007; Rammstedt and Danner 2017) or consumers' online buying impulsiveness (Turkyilmaz et al. 2015). Appendix B displays the English and German items of the Big Five Inventory that were used for Study 2 and Study 4.

John and Srivastava (1999) provide comprehensible definitions of each trait. Extraversion "implies an energetic approach toward the social and material world and includes traits such as sociability, activity, assertiveness, and positive emotionality" (p. 30). In turn, agreeableness "contrasts a prosocial and communal orientation towards others with antagonism and includes traits such as altruism, tender-mindedness, trust, and modesty" (p. 30). Conscientiousness "describes socially prescribed impulse control that facilitates task- and goal-directed behavior, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing, and prioritizing tasks" (p. 30). Neuroticism "contrasts emotional stability and even-temperedness with negative emotionality, such as feeling anxious, nervous, sad, and tense" (p. 30). Finally, openness to experience "describes the breadth, depth, originality, and complexity of an individual's mental and experiential life" (p. 30).

Multiple studies have used personality traits in IS research (e.g. Gu and Wang 2009; Hariwibowo 2017; Junglas et al. 2008; Li 2012). Exemplarily, Junglas et al. (2008) study the relationship of personality traits and concern for privacy, and they find that agreeableness, conscientiousness, and openness influence the concern for privacy. Moreover, Hariwibowo (2017) study moderating effects of the BFI in the Technology Acceptance Model (TAM) and conclude that "personality does not influence the decision to use the technology" (Hariwibowo 2017, p. 274).

Beyond personality traits, gender is an important individual characteristic in channel choices and online behavior. This is due to empirical IS studies focusing on gender differences (e.g. Aguirre-Urreta and Marakas 2010; Ogletree et al. 2014; Sonnenschein et al. 2016; Venkatesh and Morris 2000) as well as due to gender differences in personality traits (e.g. Feingold 1994; Giudice et al. 2012; Weisberg et al. 2011) within and across cultures (Costa et al. 2001; Schmitt et al. 2017). To explain these gender differences, the gender schema theory (Bem 1981) and the Bem Sex Role Inventory (Bem 1974) are used.

2.3.2 GENDER

Gender schema theory

In general, a schema in psychology is "a cognitive structure, a network of associations that organizes and guides an individual's perception" (Bem 1981, p. 355). Consequently, a gender schema, based on the gender schema theory, describes how gender schemas influence the processing of information as well as behavior and attitudes (Bem 1981). Thereby, gender schemas are based on societally constructed gender roles, i.e. the role of men and women in a society. In turn, these gender schemas influence the daily behavior of individuals in a society (Bem 1981). This relationship is illustrated in Figure 7 below.

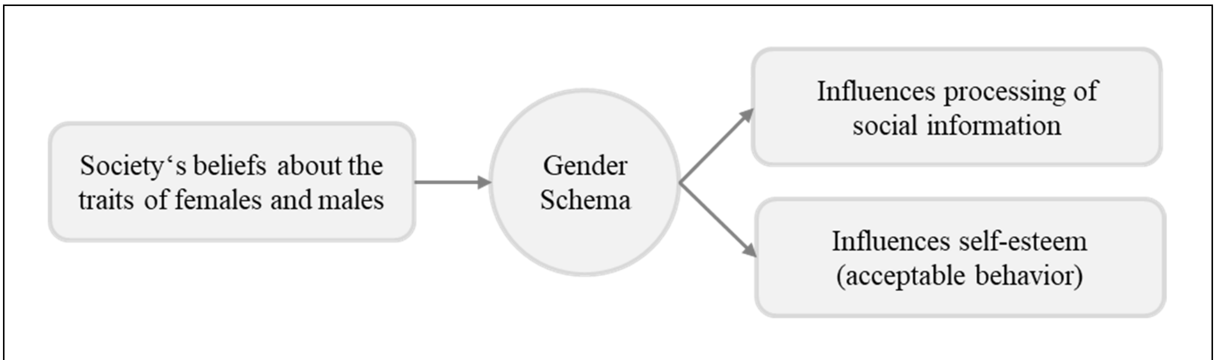

Figure 7. Gender schema theory based on Bem et al. (1981)

For example, in many societies, women are still expected to be caring, warm and understanding while men are thought to be independent, dominant and willing to take risks. This influences how we behave in our daily life and in the workplace (e.g. Venkatesh and Morris 2000). Gender schemas are difficult to assess as they are formed and applied subconsciously. Therefore, the societal beliefs about the traits of males and females are taken as an approximation which can be measured using the Bem Sex Role Inventory (BSRI).

Bem Sex Role Inventory

Gender roles can be measured among others by the Bem Sex Role Inventory (Bem 1974). It was developed by Sandra Bem and measures gender roles (masculine, feminine or androgynous) by using typical masculine or feminine characteristics. In the original version, the inventory used 20 masculine, 20 feminine and 20 neutral items (Bem 1974) and participants conducted a self-assessment of how much each trait applies to them. However, the original version is outdated with labelling traits like "intelligent" as masculine. Therefore, the inventory has been continuously updated and reassessed (Hoffmann and Borders 2001; Holt and Ellis 1998; Schneider-Düker and Kohler 1988; Sieverding 2009).

The applications of the gender schema theory and the Sex Role Inventory are endless. The theory has been used in contemporary IS studies, e.g. to explain mobile users' IT security appraisals and protective actions as well as multi-channel behavior (Hummel, Herbertz, and Maedche 2018; Sonnenschein et al. 2016). But also other researchers used gender roles to explain different forms of technology adoption (Aguirre-Urreta and Marakas 2010; Venkatesh et al. 2003; Venkatesh and Morris 2000), or texting (Ogletree et al. 2014).

Finally, we turn to theoretical and conceptual foundations of behavioral economics and nudging.

2.4 Behavioral Economics and Nudging

2.4.1 Behavioral Economics

While traditional economics presumes rational decision-makers who have all relevant information and who always aim to maximize their welfare, behavioral economics include insights from psychology and acknowledge the boundaries of rationality (Simon 1972). Behavioral economics traces back to the work of Adam Smith in the 18th century (Camerer and Loewenstein 2004), but has received greater attention with the research of Tversky and Kahneman (e.g. Tversky and Kahneman 1973, 1981), especially on their advancement of the dual process theory (Kahneman 2003).

The dual process theory assumes that the human mind is based on two systems, System 1 and System 2 (Kahneman 2003, 2011; Thaler and Sunstein 2008). On the one hand, System 1 is characterized by fast and automatic thinking, and it is often acting intuitively. On the other hand, System 2 is slow, effortful, reflective and rational. While System 2 seems to be better and less prone to errors, it needs more time and energy such that the human mind relies on System 1 for most decision during the day. Often System 1 relies on heuristics (Tversky and Kahneman 1973, 1974), also described as rules of thumb.

Behavioral economics has become such an influential sub-discipline of economics that, in 2017, Richard Thaler received the Nobel Memorial Prize in Economic Sciences for his work on behavioral economics (The Royal Swedish Academy of Sciences 2017). Among others, he received the prize for the concept of "nudging".

2.4.2 NUDGING

A nudge is "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein 2008, p. 6). In other words, decision-makers have the freedom to choose any option, but they are pushed towards one direction (Thaler and Sunstein 2003, 2008). This is referred to as "libertarian paternalism" which is "an approach that preserves freedom of choice but authorizes both private and public institutions to steer people indirections that will promote their welfare" (Thaler and Sunstein 2003, p. 179). The two terms, nudging and libertarian paternalism, are mostly used interchangeably and we refer to existing publications for a discussion on this matter (Hansen 2016; Sunstein and Thaler 2003; Thaler and Sunstein 2003).

The concept of nudging has been introduced by Richard Thaler and Cass Sunstein in 2008 in their book "Nudge: Improving Decisions About Health, Wealth, and Happiness" (Thaler and Sunstein 2008). Nudges work because of heuristics and cognitive biases in human decision-making (Thaler and Sunstein 2008), for example loss aversion, framing, or availability heuristic (Kahneman and Tversky 1979; Tversky and Kahneman 1973, 1981). Hence, nudging builds upon the dual process theory as nudges often make use of System 1 (Thaler and Sunstein 2008). Only a few nudges, in particular educative ones such as informing people of the nature and consequences of their own past choices (Sunstein 2014), deliberately aim to active System 2.

Later, other researchers have built a framework around the nudging concept called "MINDSPACE" (Dolan et al. 2012; Halpern 2016). Thereby, they claim to have gathered the nine most robust effects, and they divide them into the following cues: Messenger, Incentives, Norms, Defaults, Salience, Priming, Affect, Commitments, and Ego (see Table 1).

Table 1. Mindspace framework based on Dolan et al. (2012)	
Mindspace cue	**Behavior**
Messenger	We are heavily influenced by who communicates information to us
Incentives	Our responses to incentives are shaped by predictable mental shortcuts such as strongly avoiding losses
Norms	We are strongly influenced by what others do
Defaults	We 'go with the flow' of pre-set options
Salience	Our attention is drawn to what is novel and seems relevant to us
Priming	Our acts are often influenced by sub-conscious cues
Affect	Our emotional associations can powerfully shape our actions
Commitments	We seek to be consistent with our public promises, and reciprocate acts
Ego	We act in ways that make us feel better about ourselves

In addition to the Mindspace framework, several other approaches exist to classify nudges (Goldstein et al. 2008; Hansen and Jespersen 2013; Johnson et al. 2012; Münscher et al. 2016; Sunstein 2014). Among these frameworks it is noteworthy to highlight Sunstein (2014) who lists ten of the most important nudges. These nudges are detailed in Table 2 below.

Table 2. Overview of ten important nudges based on Sunstein (2014)		
Nudge	**Explanation**	**Examples**
Default rules	Condition that is imposed when an individual fails to make a decision	Automatic enrollment in programs, including education, health, savings
Simplification	Programs should be easily navigable, even intuitive	Simplifying an enrollment process (see also Thaler and Sunstein 2008)
Use of social norms	Emphasizing what most people do	"Most people plan to vote" or "nine out of ten hotel guests reuse their towels"
Increase ease and convenience	Reducing barriers, including time that it takes to understand what to do	Making low-cost options or healthy foods visible
Disclosure	Make information comprehensible, accessible and simple	Economic or environmental costs associated with energy use, or the full cost of certain credit cards
Warnings, graphics	Private or public warning to trigger people's attention by using large fonts, bold letters, and bright colors	E.g. as for cigarettes
Precommitment strategies	When people precommit to a certain course of action	E.g. a smoking cessation program or Save More Tomorrow program (Thaler and Benartzi 2004)

Reminders	Reminding people of doing something, timing greatly matters	By email or text message, as for overdue bills, coming obligations or appointments
Eliciting implementation intentions	Articulating the when, where and how of following through on an intention (Nickerson and Rogers 2010)	"Do you plan to vote?"
Informing people of the nature and consequences of their own past choices	Give people information about their own past choices so that their behavior can shift	"Smart disclosure" in the US and the "midata project" in the UK

Most of the examples of Sunstein (2014) as well as of Thaler and Sunstein (2008) are focusing on offline contexts. Yet, an increasing amount of decisions are taken in digital environments. To account for this trend, we finish Chapter 2 with outlining *digital nudging*. The ethics of nudging are addressed in Chapter 5.

2.4.3 Digital Nudging

In 2016, the nudging concept was transferred to digital environments, so-called "digital nudging". Digital nudging "is the use of user-interface design elements to guide people's behavior in digital choice environments" (Weinmann et al. 2016). Contrary to conventional nudging, digital nudging focuses on user interfaces. The authors suggest various applications of nudging principles and use cases/IS fields (Weinmann et al. 2016).

Beyond the above definition, two digital nudging models already exist. While Meske and Potthoff (2017) propose a "digital nudging process model" (DINU) which outlines a cycle for the design of digital nudges, also Schneider et al. (2018) developed a cyclical model to design digital nudges (see also Chapter 4.1.6).

Although digital nudging is a fairly recent concept, different types of studies were already conducted on the topic of digital nudging, such as policy papers (Gregor and Lee-Archer 2016), systematic literature reviews (Mirsch et al. 2017), research-in-progress papers (Hummel et al. 2017a; Lehrer and Jung 2017; Pahuja and Tan 2017; Stryja et al. 2017; Székely et al. 2016; Tietz et al. 2016; Weinmann et al. 2017), or even full experimental studies (Schneider et al. 2017). One example for a digital nudge is the use of warnings to prevent the purchase of incompatible digital products online (Esposito et al. 2017). Study 3 reflects on more existing related work using digital nudges.

2.5 Overview of Studies and Theoretical and Conceptual Foundations

Multi-channel management and behavior, individual differences as well as nudging and digital nudging are the overarching theoretical foundations of the respective studies of this thesis. Finally, Table 3 below provides an overview of which theoretical foundation is employed in which study and how the data of each study was collected.

Table 3. Overview of studies and theoretical foundations of this thesis

Theoretical foundations	**Study 1**	**Study 2**	**Study 3**	**Study 4**
Multi-channel behavior	Yes	Yes	No	No
Personality traits	No	Yes	No	Yes
Gender roles	No	Yes	No	No
(Digital) Nudging	No	No	Yes	Yes
Main or dependent variable	Determinants of MC behavior	Channel choice	Effect size of (digital) nudges	Sustainable product choices
Data collection	Systematic literature review	Lab experiment	Systematic literature review	Online survey experiment
Data points	53 primary publications	236 participants	100 primary publications	452 participants
Chapter of the thesis	Chapter 3		Chapter 4	

In the next chapter, we turn to the systematic literature reviews and empirical studies of this thesis.

3 Individualized Channel Choices in Digital Retail Channels

3.1 Study 1: Systematic Literature Review on Determinants of Multi-Channel Behavior[1]

3.1.1 Introduction

Just a decade ago, consumers relied on travel agents in physical branches to book flight tickets or a vacation package. With the rise of the Internet, this has drastically changed as firms increasingly offer multiple channels for their products and services (Neslin and Shankar 2009). Even more, well-integrated channels have become a competitive advantage and allow companies to differentiate themselves from their competitors (Hoong 2013). In turn, also consumers exhibit a multi-channel behavior (e.g. Cortinas et al. 2010; Verhoef et al. 2007) which renders their channel choice less predictable. This can have severe consequences for companies, for instance when consumers engage in free-riding behavior (e.g. Chiu et al. 2011; Chou et al. 2016). Thus, a thorough understanding of the determinants of multi-channel behavior is needed.

Multi-channel behavior in the context of physical products is widely researched (e.g. Inman et al. 2004; Keen et al. 2004; Thomas and Sullivan 2005), but not all of these results are transferrable to services. Thus, a separate research stream might be necessary, since services constitute an entirely different sector (Fisher 1939) and have very distinct properties (Macintyre et al. 2011). These properties involve mainly intangibility, heterogeneity, inseparability and perishability (Parry et al. 2011) which means that they cannot be touched, identically reproduced, separated from consumption, or stored. On the contrary, products are characterized, among others, by their tangibility, exchangeability and tradability, possibility of ownership and preservability (Parry et al. 2011). Moreover, products have a longer history of availability in multiple channels than services, and past research has shown that experience with a product category might be a driver of channel choice (e.g. Strebel et al. 2004). Also in terms of their influence on multi-channel behavior, products and services are assessed differently (e.g. Gupta et al. 2004). As products and services differ considerably in their properties, we would expect the determinants of multi-channel behavior to differ, too.

Some researchers examined multi-channel behavior with services, in particular in financial services (e.g. Albesa 2007; Black et al. 2002; Gensler et al. 2012). Yet, they have a different focus: Either they considered single dimensions such as the different stages of the buying process, the moderating role of service characteristics, the channel characteristics, or they touched on all relevant dimensions, but

[1] This section is based on Hummel et al. (2016)

neglect several important channel or service characteristics. In any case, they have not conceptualized the determinants of multi-channel behavior or integrated them into a comprehensive framework.

Apart from the special role of services, the scientific contributions to this topic encompass a wide range of disciplines, and they are lacking a coherent picture of the determinants of multi-channel behavior. Some researchers (Neslin et al. 2006; Neslin and Shankar 2009; Trenz and Veit 2015) provided a loose list of these determinants, but did not cluster them, show the direction of their effects, or derive them by means of a systematic literature review. Thus, we have identified a need to integrate the existing knowledge into a coherent structure such as a taxonomy or morphological box (Gregor 2006). Furthermore, we offer avenues for future research and implications for practitioners.

In sum, this study aims to conceptualize the determinants of multi-channel behavior with a special focus on services. The remainder is organized as follows: Chapter 3.1.2 recaps on the theoretical background of multi-channel behavior and describes the existing related work. Next, Chapter 3.1.3 outlines the methodological approach for the systematic literature review. Thereafter, we summarize the results including the different dimensions of the morphological box in Chapter 3.1.4. In Chapter 3.1.5, we analyze the research distribution of each dimension and offer avenues for future research for IS and marketing scholars. Finally, the study is concluded with a summary and a brief outlook on an experimental design (Chapter 3.1.6).

3.1.2 Theoretical Background

Since the turn of the millennium, multi-channel behavior has become a widely researched topic (Neslin and Shankar 2009) and several frameworks aim to explain multi-channel management and multi-channel behavior (Black et al. 2002; Dholakia et al. 2010; Neslin and Shankar 2009). One area of research is consumer analysis and segmentation. For instance, researchers have found that multi-channel consumers increase sales (Kumar and Venkatesan 2005; Kushwaha and Shankar 2013), are more loyal (Ansari et al. 2008; Shankar et al. 2003), and more innovative (Farag et al. 2006). Another area, which is also the focus of this study, comprises the influencing factors of multi-channel behavior. Based on prior research, multi-channel behavior is influenced by several factors, namely the stage of the buying process, channel attributes, consumer characteristics, and product attributes (e.g. Neslin et al. 2006; Neslin and Shankar 2009; Trenz and Veit 2015).

A buying process consists of several stages and various researchers identified stage-channel associations (e.g. Gensler et al. 2012; Verhoef et al. 2007). For instance, many consumers associate the search stage with the online channel, but the purchase stage with the store (Verhoef et al. 2007). Moreover, there are channel spillover effects when a consumer chooses the same channel in a later stage of the buying process (e.g. Gensler et al. 2012).

Prior literature also documents numerous channel characteristics (see Neslin et al. 2006 for a partial list). For instance, perceived convenience (e.g. Gensler et al. 2012; Verhoef et al. 2007), perceived risk (e.g. Black et al. 2002; Verhoef et al. 2007), privacy (Albesa 2007; Verhoef et al. 2007), perceived price (e.g. Gensler et al. 2012; Venkatesan et al. 2007), social interaction (e.g. Albesa 2007; Frambach et al. 2008), product assortment (e.g. Melis et al. 2015; Noble et al. 2005), service (e.g. Burke 2002; Konuş et al. 2014), immediate availability (e.g. Venkatesan et al. 2007), negotiation possibilities (e.g. Verhoef et al. 2007), accessibility (e.g. Black et al. 2002; Frambach et al. 2008), and channel design (e.g. Schoenbachler and Gordon 2002) are determinants of multi-channel behavior. Table 4 provides an excerpt of the research focusing on multi-channel behavior and consumers' channel choice.

Table 4. Subset of related work on multi-channel behavior

Reference	**Dependent variable**	**Channels**	**Several Stages**	**Channel charact.**	**Demo-graphics**	**Product charact.**
Tse and Yim (2001)	Channel choice	Store, Internet	-	X	-	-
Black et al. (2002)	Channel choice	Internet, branch, call center	-	X	X	X
Schoenbachler and Gordon (2002)	Channel choice	Store, catalog, Internet	-	X	X	X
Gupta et al. (2004)	Channel switching	Store, Internet	X	X	X	X
Keen et al. (2004)	Channel choice	Store, catalog, Internet	-	X	X	X
McGoldrick and Collins (2007)	Attitude score for certain channels	Store, Internet, catalog	-	X	X	X
Konus et al. (2008)	Channel utility	Store, Internet, catalog	X	X	X	X
Cortinas et al. (2010)	Entropy of multi-channel behavior	Branch, Internet, call center, ATM	X	-	X	X
Gensler et al. (2012)	Channel choice intention	Branch, Internet, call center, ATM	X	X	X	-
De Keyser et al. (2015)	Channel usage	Store, Internet, call center	X	X	X	X

Note: The terms branch and store are based on the terminology of the respective primary publication. The terms are therefore used synonymously throughout this thesis.

Almost all studies include individuals' demographics. Mostly, the studies examine age, gender, and income, but occasionally also consider education, occupation, geo-demographics (e.g. Inman et al. 2004), or study psychographics when examining consumer characteristics (e.g. De Keyser et al. 2015; Konus et al. 2008). Various researchers argue that attitude (e.g. Keen et al. 2004; Konus et al. 2008), loyalty (e.g. Konus et al. 2008; Melis et al. 2015), and goals (e.g. Balasubramanian et al. 2005) are also determinants of multi-channel behavior. For instance, Konus et al. (2008) document that the attitude towards a specific channel influences the choice of it.

Another strong indicator of channel choice is a consumer's prior experience. Thereby, this comprises the consumer's experience with the channel (Ansari et al. 2008; Dholakia et al. 2005; Frambach et al. 2008), the Internet (Ansari et al. 2008; Farag et al. 2006; Frambach et al. 2008), (home) shopping experience (Farag et al. 2006; Schoenbachler and Gordon 2002), experience with the product or the firm (Nicholson et al. 2002; Strebel et al. 2004; Sullivan and Thomas 2004), and the time and quality of the experience (Ansari et al. 2008; Schoenbachler and Gordon 2002).

Finally, product categories are studied by researchers in the area of multi-channel behavior. Products and services can be classified according to the purchase frequency (e.g. Inman et al. 2004; Keen et al. 2004; Konus et al. 2008), transaction volume (e.g. Black et al. 2002; Keen et al. 2004; Venkatesan et al. 2007), complexity (e.g. Black et al. 2002; Inman et al. 2004; Konus et al. 2008), and search vs. experience goods (e.g. Gupta et al. 2004; Heitz-Spahn 2013; Maity and Dass 2014). Similar to stage-channel associations, product-channel associations link certain product types with certain channels (e.g. Cortinas et al. 2010; Gensler et al. 2012).

The related work shows that the determinants of multi-channel behavior are well-researched. Yet, prior work is scattered around a variety of studies and a coherent structure is missing. Furthermore, the contributions fall into the context of products, but channel preferences might be specific to context (Wood and Neal 2009) as well as to product or service characteristics. Thus, this work represents a meaningful complement to existing literature by proposing a structure for the determinants of multi-channel behavior and by focusing on context of services.

3.1.3 Research Methodology

For the conceptualization of multi-channel behavior and the development of the morphological box, we conducted a systematic literature review following the suggestions of Webster and Watson (2002). The literature review is organized around the concept of multi-channel behavior. In this literature review, we only considered peer-reviewed articles from journals. As a starting point, we considered various articles (e.g. Black et al. 2002; Neslin et al. 2006; Schoenbachler and Gordon 2002) which include an overview of multi-channel behavior. Each of them is referenced more than 300 times by other researchers which provides sufficient evidence of their representativeness for the topic.

Drawing on these articles, we developed several keyword-based search strings and used them in the online databases AIS library, ScienceDirect, EBSCOhost and Google Scholar to find more articles relevant for the conceptualization of multi-channel behavior. The search strings include the terms "multi-channel" AND "consumer behavior", "multi-channel" AND "purchase decisions" OR "multi-channel behavior", or just "channel choice" and yield between 300 and 1,000 articles per search string and database. For example, "multi-channel" AND "consumer behavior" yields 341 hits in ScienceDirect between 1999 and 2016. Most of these studies, however, focus on products. Thus, in order to find more literature on services in general and financial services in particular, we added the terms "services", "financial services" or "banking" to the search string (e.g. "multi-channel" AND "consumer behavior" AND "services"). Financial services were included in the search string as they are an important domain within the overall services industry and they have a long history of multi-channel management (Hoehle et al. 2012). We used these keywords because they describe the relevant aspects of our research goal, namely consumer behavior in a multi-channel context with a focus on services. For the term "multi-channel", we utilized different notations such as "multichannel" or "multi-channel".

Next, we aimed to narrow down the results and therefore developed further inclusion and exclusion criteria. In particular, we constrained our search to articles published between 1999 and 2016, because the Internet, especially as a purchasing channel, was not prevalent in the early 1990s and before. In addition, the results on determinants of multi-channel behavior might not be comparable across several decades. We also excluded articles because (a) they examine the behavior within a single channel (e.g. online) and not in a multi-channel context, (b) they treat task-channel fits and not the choices during a purchasing process, or (c) they do not aim to explain consumer behavior, but only the consequences of it. Articles were included when they cover the search and/or purchase of goods and services in a multi-channel context. Thus, we mainly considered articles that utilize dependent variables such as channel choice, channel usage, or intentions to use a channel. Overall, 53 primary publications (see Appendix D) were incorporated into the final morphological box.

In the end, the results of the literature review were conceptualized in a morphological box similar to the work of Meth (2013). We deliberately decided to develop a morphological box rather than a taxonomy, as many different dimensions are discussed in the literature which have characteristics that are not always mutually exclusive or collectively exhaustive (Nickerson et al. 2013). We have also considered flow charts such as the Conceptual Model of Post-Adoptive Behavior by Jasperson et al. (2005), yet these would have focused on one purchasing process only. Moreover, the morphological box is more flexible to the diverse range of influences on multi-channel behavior. The dimensions of the morphological box are derived from the related work (e.g. Neslin et al. 2006; Neslin and Shankar 2009) and were subsequently refined during the systematic literature review following the suggestions of Nickerson et al. (2013).

In a second step, we counted the frequency of characteristics under examination (see Chapter 3.1.5) to identify directions for future research. We included a dimension or characteristic whenever it was examined as a dependent or independent variable in the model presented in the primary publications. Thereby, it is irrespective if the variable proved to be significant or not. Also including statistically insignificant variables in the analysis will provide a more complete picture on the entire research field and thus, will prevent us (and other researchers) to incorrectly identify research gaps that have already been studied in the literature. Lastly, we counted a dimension or characteristic whenever it was included in a conceptual or theoretical framework (e.g. Schoenbachler and Gordon 2002).

3.1.4 Results

Figure 8 displays the results of our literature review (colors used for stylistic reasons only). As indicated below, the dimensions of context, consumer and product influence a consumer's multi-channel behavior. In the following, we discuss the impact of each dimension and their characteristics in detail.

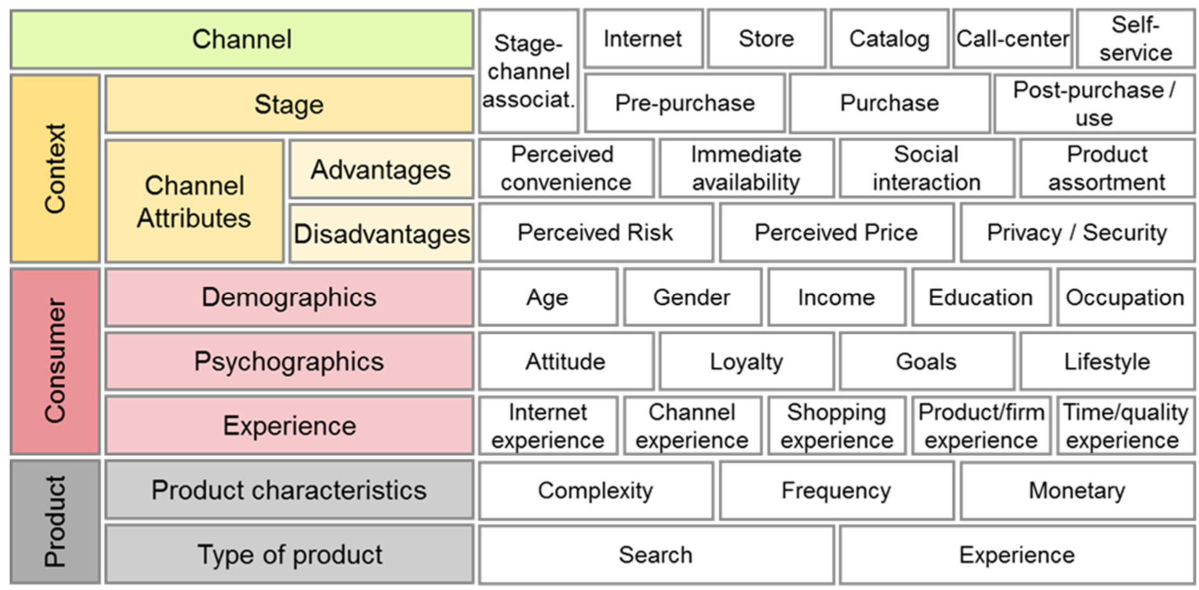

Figure 8. Morphological box of determinants of MC behavior

Channel

Channel describes the distribution channels that are chosen to search for, purchase or use a product or service. When multiple channels are combined within one purchasing process, it is denominated as multi-channel choice, multi-channel behavior or multi-channel choice behavior (see Chapter 2.1).

Context

As mentioned in the related work section, stage-channel associations link a stage of the purchasing process with a certain channel. For instance, the online channel is preferred for the search whereas many purchases still occur in the store or branch (Verhoef et al. 2007). Gensler et al. (2012) find similar associations in a retail banking context. The channel is also affected by channel spillover (Gensler et al. 2012) or channel lock-in (Verhoef et al. 2007), when using a channel in one stage is affecting the choice of the same channel in another stage. In particular, channel choice in the pre-purchase and purchase stage are closely aligned (e.g. Gensler et al. 2012). Hence, it is insufficient to examine a single stage alone. Rather, the entire purchase history needs to be considered.

Like Verhoef et al. (2007), we group the channel characteristics into advantages and disadvantages. All advantages are positively related to consumers' channel choice. Thus, the more consumers perceive a certain channel as convenient, the more likely they will choose this channel during the purchasing process. The perceived convenience is one of the main drivers of choosing digital channels (e.g. Albesa 2007; Gensler et al. 2012). In this context, immediate availability disfavors the online channel or catalog as consumers cannot take possession of the products immediately but have to wait for shipment (Venkatesan et al. 2007; Wolfinbarger and Gilly 2001). Moreover, channels are equipped with different product assortments and possibilities for social interactions. For example, consumers with a preference for social interactions are more likely to choose the offline channel, as they can come in direct contact with other consumers or salespersons when visiting a store (e.g. Balasubramanian et al. 2005). Similar to the social interaction, the product assortment influences consumers' channel choice. However, the results on the impact of the product assortment are somewhat mixed. While Noble et al. (2005) cannot support any influence, Verhoef et al. (2007) find a significant positive effect of product assortment on consumers' selection of digital channels. Other studies (e.g. Konuş et al. 2014; Melis et al. 2015) support the importance of product assortment.

While factors such as convenience, immediacy, social interaction or product assortment have a positive influence on the respective channel choice (see above), consumers are negatively influenced by factors such as perceived risk, perceived price, and privacy (see below). The higher the perceived costs of a channel will be, the more likely the consumer chooses a different channel. Thereby, costs do not only cover monetary expenditures, but also search costs, switching costs, or travel costs (e.g. Dholakia et al. 2005; Noble et al. 2005). Like perceived risk, the perceived price correlates negatively with the choice of that channel (Verhoef et al. 2007). On the other hand, Gensler et al. (2012) find no influence of the perceived price on channel choice. Privacy, defined as „the users' worries about the acquisition and subsequent use of information generated or acquired about them" (Albesa 2007, p. 495), is particularly applicable to digital channels. Although some studies argue that privacy was not an issue in their study (Bellman et al. 1999), other studies observe negative influences on the respective channel choice (Burke 2002; Verhoef et al. 2007). If consumers do not feel save when providing their payment details in digital channels, they might prefer to buy the products directly in a store. Security is subject to similar mechanism as privacy (Hoehle and Huff 2009).

Consumer

A second dimension influencing consumers' channel choice comprises consumer characteristics. The influence and direction of demographics on channel choice is, at least, disputable. In sum, many researchers come to the conclusion that younger consumers prefer digital over offline channels (e.g.

Black et al. 2002; Strebel et al. 2004; Venkatesan et al. 2007). Also, income (Black et al. 2002), education (Strebel et al. 2004) and gender (Venkatesan et al. 2007) are thought to have an influence on consumer's channel choice, i.e. males with a higher income and higher education are more likely to choose digital channels. On the other hand, many other researchers believe that demographics are not a reliable differentiator for channel choice (e.g. Cortinas et al. 2010; Konus et al. 2008). Rather, lifestyle is thought to be a more fitting concept to segment consumers than demographics. For instance, individuals following a "technological lifestyle" favor digital channels (Bellman et al. 1999).

Although there is no unanimously shared definition of psychographics (Wells 1975), the term encompasses mostly the study of "values, attitudes, and personality traits" (Wells 1975, p. 197). Within this umbrella term, attitude, loyalty and goals are determinants of the channel choice. For instance, Konus et al. (2008) demonstrate the importance of attitude on channel choice, while economic theory has identified attitude to play a key role in choice behavior (McFadden 2001). When it comes to goals, it is most important whether consumers are seeking an enjoyable experience (hedonic) or whether they are looking for the best deal (utilitarian). While digital channels largely support the attainment of functional goals (i.e. efficiency), stores and catalogs are the preferred channels for hedonic objectives (e.g. Balasubramanian et al. 2005).

A strong determinant of channel choice is the experience of a consumer. The more experienced a consumer is with a certain channel and the better and more recent these experiences are, the more likely the consumer will choose that channel again. As stated in Chapter 3.1.2, experiences include experiences with a channel, the Internet in general, (home) shopping experience and experience with the product or the firm.

Product

Product categories have been identified to have a moderating role on channel choice. They can be categorized according to product complexity, purchase and usage frequency as well as transaction volume. Products with a high purchase frequency and a low transaction volume (e.g. books) are more likely to be bought through digital channels (e.g. Gupta et al. 2004), whereas complex experience goods are more prevalent in the offline channel (e.g. Maity and Dass 2014). High purchase frequency is also associated with multi-channel behavior (Kumar and Venkatesan 2005). Services again have their own set of determinants that are similar, but not equal to their product counterparts (see Chapter 3.1.1). Finally, researchers classify products and services according to experience vs. search. Experience products (e.g. wine) are less likely to be obtained through digital channels than search products such as books (Gupta et al. 2004). Other researchers come to similar conclusions (e.g. Heitz-Spahn 2013; Maity and Dass 2014).

3.1.5 Research Distribution and Services Relevance

Having gathered a clear understanding of the factors influencing consumers' channel choice, we analyzed the examined literature with regard to the frequency of studies using these constructs. By conducting such an analysis, we aimed to identify relevant research gaps. We summarized the results of the frequency analysis in Figure 9. Hereby, the numbers in brackets indicate the frequency of the respective aspects studied by researchers. The color-coding provides a visual help. Products (i.e. the left side of Figure 9) have been studied 45 times whereas services have only been considered 8 times in the past. Even a dedicated search string for services (as outlined in Chapter 3.1.3) could not resolve this imbalance.

It is apparent that the Internet and the store are studied extensively. Only a limited number of studies involve self-service terminals, such as ATMs, or call centers. Concerning the stage of the buying process, most researchers dedicate their work to the pre-purchase and purchase stage, for instance by studying research shopping (Verhoef et al. 2007), i.e. searching in one channel and buying in another one. Less attention is drawn to the post-purchase phase, e.g. when consumers use services related to the product or provide feedback on it. When comparing the channel attributes, there is a clear focus on the perceived benefits. Yet, this may be due to the nature of focusing on the enablers of channel choice and not its inhibitors. Product characteristics have been examined less frequently compared with the other dimensions. This is despite their known moderating role (e.g. Kushwaha and Shankar 2013). Finally, the dimensions of consumer characteristics, demographics and experience are studied extensively, while studies on psychographics remain rare.

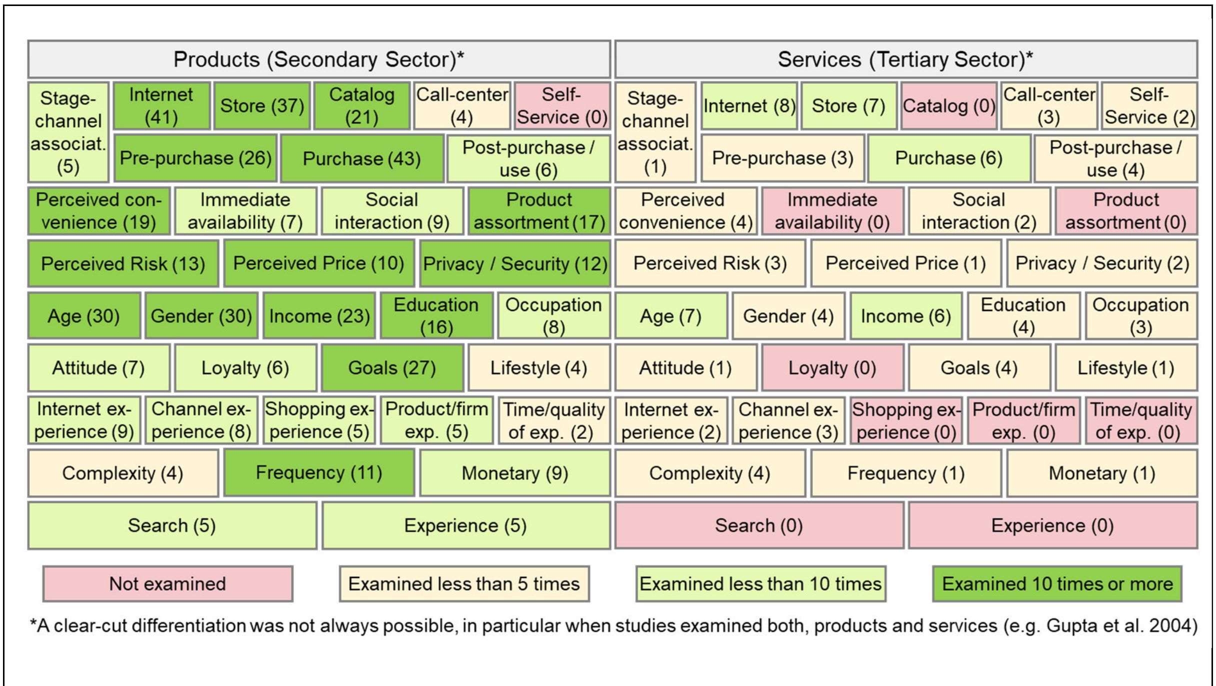

Figure 9. Morphological box of determinants of MC behavior including research coverage

When distinguishing between products and services, several differences are apparent. First, the catalog and the call center play a minor role in services as most services are branch- or Internet-based. The pre-purchase phase also seems to be of less importance. In contrast, the post-purchase stage is relatively important in services as most (financial) services have a longer life cycle. Perceived benefits have been reviewed less frequently than perceived costs for services. The same holds true for psychographics and experience factors. Finally, also service characteristics are yet to be explored in greater detail (Gensler et al. 2012), especially since they can also be classified into different categories (Durkin et al. 2008).

What is the benefit of the morphological box and the frequency analysis? We demonstrate implications for researchers and practitioners. Researchers can benefit from avenues for future research. Based on the under-researched areas in services, we derive three exemplary research questions that enhance the knowledge of multi-channel behavior in the service industry.

A channel's capability for social interaction plays an important role for products. Surprisingly, it has to our knowledge only been considered twice in a multi-channel context in the service industry (Black et al. 2002; Lamberti et al. 2014). Banking branches and stores offer possibilities to interact socially with the providers or other consumers. It is reasonable to assume that the social interaction is a major reason for consumers to choose the offline channel. Hence, we propose:

RQ1*: How does a channel's capability for social interaction affect consumers' channel choice in the service industry?*

Loyalty has not been studied in the context of services, although it is ascribed a central role in banking (Du Toit et al. 2015). In the dataset of Cortinas et al. (2010), the average relationship of consumers with their banks was more than 14 years. Loyalty can be divided into channel loyalty (e.g. Thomas and Sullivan 2005) and brand or firm loyalty (e.g. Konus et al. 2008), and it is documented to have an impact on channel choice for products. Consequently, we suggest:

RQ2*: How does channel and firm loyalty affect consumers' channel choice in the service industry?*

Product categories have a moderating role on channel choices (see above). This relationship has yet to be researched in financial services which can be segmented along different dimensions such as complexity, frequency or level of contact (Durkin et al. 2008). Other researchers have already suggested to study the role of service categories in banking (Gensler et al. 2012). Therefore, we hypothesize:

RQ3*: How is channel choice moderated by different service categories of financial services (e.g. savings and investment)?*

Practitioners can use the morphological box as a guideline to evaluate their channels and to analyze the match with their consumer base. First, they have to assess which channels they are offering and how these channels are positioned within the firm. Second, they should segment their consumers along individual characteristics, such as demographics, psychographics and experience (see dimension "consumer" in the morphological box). This can be done, for instance, by defining target consumers or segments. Third, they should analyze if their channels match the respective consumer segments. If not, marketing managers can actively steer consumer behavior by implementing measures which represent characteristics of the channel attributes. For example, the firm could offer the possibility to order online but to pick-up the order in the store, thus extending the breadth of the online product assortment to physical stores. Moreover, other measures could be taken to promote the channel advantages and to reduce the channel disadvantages (e.g. refund money of fraudulent transactions) for certain consumer segments. Finally, practitioners can use the morphological box to review their product portfolio and test it for stage-channel and product-channel associations (Gensler et al. 2012; Verhoef et al. 2007).

3.1.6 Conclusion and Outlook

This work studies the determinants of multi-channel behavior. After conducting a systematic literature review, a morphological box is developed that structures multi-channel behavior according to the dimensions of context, consumer and product. Subsequently, the research frequency of the morphological box is derived for products and services. It documents under-researched areas in services. Based on these areas, we derived implications for researchers and practitioners.

To evaluate the results of our study, it is important to reflect on its limitations. Only 53 primary publications were considered in the systematic literature review and it is likely that there exist further studies that examine multi-channel behavior. With more studies, the morphological box could be more detailed, and the research frequency analysis could have led to a different color-coding. Further, we only considered studies that investigate the channel choice in a multi-channel context for searches or purchases. More determinants could be transferred from research on adoption of single channels (e.g. the online channel) or from multi-channel behavior for tasks (e.g. bank transfer online or in a branch).

In a next step, we reflect on a potential experimental design. The results could be used for a laboratory experiment that aims to intervene in the online banking (channel) during the post-purchase stage. Thereby, it could examine the impact of social interaction, product categories, and consumer characteristics on consumers' channel choice. As previous studies demonstrate gender-related differences, the experiment could aim to nudge women with a preference for the branch towards digital channels.

In this experiment, the participants could be shown the user interface of a regular online banking, where they have to perform tasks, such as checking their portfolio performance or initiating a transfer. Each time, they could be given the choice which channel to use for the task whereas each channel could have different representations. The branch could be represented by making an appointment with the bank adviser, the telephone banking by entering and dialing a number, or the online channel by the user interface of the online banking. Thereby, each channel could have different possibilities for social interactions.

To nudge the participants towards a certain channel, the effect of priming (Dolan et al. 2012; Palmer 1975) could be used (see Dolan et al. 2012 for a definition). The priming could be operationalized by exposing the subjects to images or representations of the respective channels before the task. In other contexts, priming has proven to be a successful influence (Thaler and Sunstein 2008). In practice, priming could be imagined as an advertisement that consumers remember when thinking about their channel choice. Marketing communications have already shown to be influencers of channel choice (e.g. Venkatesan et al. 2007). Thus, the nudge could be used to investigate RQ1 how a channel's capability for social interaction affects consumers' channel choice.

Beyond RQ1, the experiment could generate interesting findings on how much the channel choice of consumers can be influenced by the design of channel and how it is moderated by the product category. Additionally, the experiment could be useful for banks to increase the efficiency of their branch staff by nudging consumers towards digital channels for simple tasks. The staff could then be able to focus exclusively on sales activities and is less occupied with administrative activities.

3.2 Study 2: The Role of Personality Traits and Gender Roles in Digital Retail Channels[2]

3.2.1 INTRODUCTION

The rise of new technologies led to the development of new retail channels, such as the online or mobile channel which are collectively referred to as digital channels. The new digital channels offer consumers a multitude of options to search, purchase, and use products and services (Verhoef et al. 2007). Yet, in a recent study, only 7% of the consumers were "online-only shoppers" while the majority of the consumers (73%) relied on multiple channels during their shopping journey (Sopadjieva et al. 2017). An increase in online-only shoppers would reduce free-riding and channel-switching (e.g. Chou et al. 2016) and lead to substantial monetary savings for channel providers as transactions in physical channels are more expensive (PwC 2012). In addition, also consumers would benefit from an increased online usage, as using multiple channels could lead to prolonged purchasing processes or competing information and experiences in different channels (Brynjolfsson et al. 2013; Rawson et al. 2013).

One possible solution to this dilemma is individualizing the design of digital channels. Especially by implementing an individualized user interface, which can be more effective than a standard interface for the whole population (Nov, Arazy, López, et al. 2013), the negative consequences can be outweighed. Previous studies have shown that individualizing the UI according to the individual user or consumer characteristics increases user's online contribution (Nov, Arazy, López, et al. 2013) or participation (Nov, Arazy, Lotts, et al. 2013). Moreover, a well-designed individualization might increase the use of new technology (Oulasvirta and Blom 2008). Therefore, also the usage of digital channels could be increased by individualizing them according to the individual consumer characteristics.

To be able to design and to individualize digital channels, the interplay between individual characteristics and channel characteristics is needed. Thereby, information systems and marketing scholars have analyzed multi-channel behavior and detected a variety of channel characteristics, such as perceived risk (Gensler et al. 2012; Verhoef et al. 2007), perceived benefits (e.g. Frambach et al. 2008), or trust (Kim et al. 2008; Yoon 2002), that function as determinants of multi-channel behavior. In addition, each study assessed demographical factors to analyze individual differences. Yet, demographics alone are not suitable to explain individual differences in channel choices (Cortinas et al. 2010; Konus et al. 2008). However, and with regard to the psychological literature, other individual characteristics might be more applicable, such as personality traits and gender roles. They have served as explanatory or moderating variables in different contexts of online behavior before (e.g. Barnett et al. 2015; Cyr et al. 2017; Johnston et al. 2016; Venkatesh and Morris 2000). Moreover, the influence of personality traits or gender roles on channel choices has not been covered in the literature. Several

[2] This section is based on Hummel, Vogel, Schacht et al. (2018)

literature reviews on channel choices do not cover personality traits or gender roles (e.g. Hummel et al. 2016; Neslin et al. 2006).

Personality traits and gender roles can be assessed through different inventories such as the prominent Big Five Inventory (McCrae and John 1992) or the Bem Sex Role Inventory (Bem 1974). The Big Five Inventory is based on five traits, namely extraversion, agreeableness, conscientiousness, neuroticism, and openness. Personality traits have an influence in various fields of IS Research, e.g. in various forms of decision support (e.g. Bansal et al. 2010), to advance the TAM (Svendsen et al. 2013) or the Theory of Acceptance and Use of Technology (Barnett et al. 2015). The same accounts for gender roles which are used in IS theories, too (e.g. Cyr et al. 2017; Venkatesh and Morris 2000). Also from a practical point of view, it is important to understand their role in channel choices as companies nowadays are able to assess personality traits based on social media data (Markovikj et al. 2013). Indeed, some researchers have addressed personality traits and gender roles in online contexts, but they did it on a qualitative level (Florenthal and Shoham 2010; Pieterson and van Dijk 2007) or they considered a different dependent variable, such as online impulse buying behavior or the intention to disclose health information (Bansal et al. 2010; Bosnjak et al. 2007; Turkyilmaz et al. 2015).

Therefore, extending existing decision-making models in the periphery of channel choices with personality traits and gender roles is important to derive insights for the individualization of digital channels. Among a variety of such models (Chou et al. 2016; Gupta et al. 2004; Kim et al. 2008), we identified the basic theoretical framework of Kim et al. (2008) to be particularly applicable. We extend this model in two ways: with personality traits and gender roles. Overall, we propose the following research question:

***Research Question**: What is the effect of personality traits and gender roles on perceived risk, trust, and perceived benefits?*

To answer the research question, we conducted a laboratory experiment with 236 participants in a German university laboratory using a multi-channel banking context. The participants had to browse a fictitious banking website and to contract a student loan. Finally, they filled out a survey with the respective items. The data is analyzed using the covariance-based approach of Structural Equation Modeling.

Our study provides several contributions to the IS literature. First, it highlights the role of personality traits and gender roles in channel choices and extends an existing decision-making model (Kim et al. 2008). We find that agreeableness, neuroticism, extraversion, masculinity and femininity are important antecedents of the channel determinants of perceived risk, trust, and perceived benefits. Thereby, we were also able to replicate the basic theoretical framework of Kim et al. (2008), which is originally based on a survey, in an experimental context. Finally, we generate empirical knowledge that can be used for the design of digital channels. For example, practitioners can use our results as a basis for the individualization of their digital channels by highlighting the benefits of digital channels particularly to introverted consumers or consumers with low neuroticism, or by presenting trust-building seals (e.g. Mousavizadeh et al. 2016) to consumers with high masculinity.

The remainder of the study is structured as follows: In Chapter 3.2.2, we describe prior work on determinants and models of channel choices as well as inventories of personality traits and gender roles. Afterwards, we derive the hypotheses and synthesize them in a research model (Chapter 3.2.3). Chapter 3.2.4 outlines the experimental setup and the context of financial services as well as the data analysis methodology. Chapter 3.2.5 shows the results of the measurement model and structural model, which are then discussed in Chapter 3.2.6. Finally, Chapter 3.2.7 concludes the study with the contributions, the limitations, and an outlook on future research.

3.2.2 Theoretical Background

Determinants of multi-channel behavior

Multi-channel behavior of consumers provides the context for our study as using multiple channels has become the standard case for most consumers (Sopadjieva et al. 2017). Within this context, several studies have reviewed the determinants of multi-channel behavior and categorized them into different dimensions (Hummel et al. 2016; Neslin et al. 2006; Trenz and Veit 2015). While Trenz and Veit (2015) categorize the determinants into four groups (channel determinants, purchase specifics, external influences, and individual differences), Hummel et al. (2016) identify the dimensions of context (including channel determinants), consumer and product. According to the literature reviews, particularly channel determinants play a decisive role in channel choices. Hence, they are usually integrated into channel choice models or decision-making models.

Based on a non-systematic literature review on channel choices, we reviewed at least ten different models of channel choices or intention to use a channel (e.g. Chou et al. 2016; Fang et al. 2006; Gensler et al. 2012; Graupner and Maedche 2015; Gupta et al. 2004; Kim et al. 2008). Most models have in common that they use a basic set of main constructs that are anteceded by a variety of more context-dependent constructs, such as perceived privacy protection or privacy concerns (Kim et al. 2008; Ozdemir et al. 2017). One of the most often used models is presented by Kim et al. (2008) with more than 2,000 citations. Their core model theorizes that purchase intentions are based upon perceived risk, perceived benefits and consumer trust. For instance, perceived risk can be defined as "a consumer's belief about the potential uncertain negative outcomes from the online transaction" (Kim et al. 2008, p. 546), and their study shows that perceived risk has a strong impact on consumers' purchasing decisions. This is in line with other studies which show that channel choices are largely determined by factors such as perceived risk, privacy concerns or trust (e.g. Gensler et al. 2012; Gupta et al. 2004; Verhoef et al. 2007).

Beyond these determinants, also individual consumer characteristics, in particular demographics, have been studied widely as determinants of multi-channel behavior (see literature reviews Hummel et al. 2016; Neslin et al. 2006; Trenz and Veit 2015). Mostly, only papers from the early 2000s find demographical differences (Black et al. 2002; Strebel et al. 2004), and by today, several studies reach the result that demographics alone are not effective in explaining channel choices (e.g. Cortinas et al. 2010; Konus et al. 2008). Hence, other individual characteristics such as personality traits and gender roles might be better suited in this context. We decided to focus on personality traits and gender roles as they have proven to be important in different online behavior contexts before (e.g. Barnett et al. 2015; Cyr et al. 2017; Johnston et al. 2016; Venkatesh and Morris 2000) but have been left out as individual differences by the channel choice literature (Hummel et al. 2016; Neslin et al. 2006; Trenz and Veit 2015).

Personality traits and gender roles

There are different definitions of personality traits (see Chapter 2). For example, Allport (1961) describes personality traits as a "neuropsychic structure having the capacity to render many stimuli functionally equivalent, and to initiate and guide equivalent (meaningfully consistent) forms of adaptive and expressive behavior" (Allport 1961, p. 347). Other researchers define personality traits as "an individual's dispositions or tendencies that lead to certain attitudinal and behavioral patterns across situations" (Junglas et al. 2008; McCrae and Costa 1987). A common denominator of all definitions is the finding that personality traits are stable characteristics that allow to understand, explain and predict the behavior of individuals (Stemmler et al. 2011). In other words, the definitions assume behavioral patterns and thus a certain stability across situations. Personality traits are formed at younger ages, remain somewhat stable in the following years, and are subject to change in the old ages again (Specht et al. 2011).

Several inventories exist to classify personality traits. The most prominent one is the Big Five Inventory (McCrae and John 1992), namely extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. John and Srivastava (1999) provided comprehensible definitions for each trait. Thereby, *extraversion* "implies an energetic approach toward the social and material world and includes traits such as sociability, activity, assertiveness, and positive emotionality" (p. 30). In turn, *agreeableness* "contrasts a prosocial and communal orientation towards others with antagonism and includes traits such as altruism, tender-mindedness, trust, and modesty" (p. 30). Moreover, *conscientiousness* "describes socially prescribed impulse control that facilitates task- and goal-directed behavior, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing, and prioritizing tasks" (p. 30). *Neuroticism* "contrasts emotional stability and even-temperedness with negative emotionality, such as feeling anxious, nervous, sad, and tense" (p. 30). Finally, *openness* "describes the breadth, depth, originality, and complexity of an individual's mental and experiential life" (p. 30). The Big Five Inventory has also been used in the past to advance IS theories (e.g. Junglas et al. 2008).

In addition to personality traits, we consider gender roles due to gender differences in personality traits (e.g. Giudice et al. 2012; Weisberg et al. 2011). IS researchers have frequently used gender differences as an explanatory factor in explaining technology acceptance (e.g. Cyr et al. 2017; Sonnenschein et al. 2016; Venkatesh and Morris 2000), or suggest to do so in future research (Krasnova et al. 2017). To account for this stream, we refer to an existing gender role inventory, the Bem Sex Role Inventory (Bem 1974). It uses masculine, feminine and neutral characteristics to classify different sex types. The original questionnaire consisted of 20 masculine, 20 feminine and 20 neutral characteristics that can be used to derive different sex-types, especially feminine and masculine. Feminine-typed individuals score high on characteristics like "affectionate", "sensitive to the needs of others" or "loves children" while masculine-typed persons are associated with being "dominant", "forceful" or "willing to take risks" (Bem 1974, p. 156). The inventory of Bem (1974) has been refined with more up to date characteristics (Hunt et al. 2007; Sieverding 2009) and was also used (Aguirre-Urreta and Marakas 2010), or at least referenced (Venkatesh and Morris 2000) in IS studies in the past. We build on these studies and incorporate personality traits and gender roles in the research streams of channel choices.

Personality traits in online environments

Personality traits and gender roles have rarely been used in the channel choice literature. However, they were employed outside of the context of channel choices to investigate consumer behavior in online environments in general. Table 5 shows an exemplary subset of prior research using personality traits and gender roles in online environments.

Table 5. Related work on personality traits and gender roles in online environments

Study	Context	Dependent variable	Type of study	Personality traits or gender role	Signific. effect
Wang et al. (2006)	E-Commerce	Intention to shop online	Quantitative (Survey)	Openness to experience, risk-taking propensity	Yes
Bosnjak et al. (2007)	E-Commerce	Intention to shop online	Quantitative (Survey)	Big Five Inventory	Yes
Pieterson and van Dijk (2007)	Government services	n/a	Qualitative (Interviews)	Not specified	n/a

Florenthal and Shoham (2010)	E-Commerce	Channel preferences	Qualitative (Framework)	Not specified	n/a
Bansal et al. (2010)	Health	Intention to disclose health information	Quantitative (Lab experiment)	Big Five Inventory	Mixed
Liu et al. (2013)	E-Commerce	Urge to buy impulsively	Quantitative (Survey)	Impulsiveness, normative evaluation, instant gratification	Yes
Turkyilmaz et al. (2015)	E-Commerce	Online impulse buying	Quantitative (Survey)	Big Five Inventory	Yes
Rodríguez-Torrico et al. (2017)	E-Commerce	Device usage (online/mobile)	Quantitative (Survey)	Impulsiveness, need for touch	Yes
This study (2018)	Financial services	Channel choice	Quantitative (Lab experiment)	Big Five Inventory, Bem Sex Role Inventory	See below

Some researchers in the IS domain have studied personality traits and gender roles. Yet, a systematic investigation is missing, and previous research suffers from several shortcomings. Therefore, we see room for differentiation in several dimensions. Firstly, some researchers have performed qualitative studies by conducting interviews (Pieterson and van Dijk 2007) or developing a framework without evaluating it (Florenthal and Shoham 2010). Secondly, some studies (e.g. Liu et al. 2013; Rodríguez-Torrico et al. 2017; Wang et al. 2006) did not use established inventories of personality traits such as the Big Five Inventory, which would be helpful in terms of the reliability of constructs, or when different studies want to be compared. Thirdly, it is important to notice that past studies assessed intentions (Bansal et al. 2010; Bosnjak et al. 2007; Liu et al. 2013) or a different dependent variable (Rodríguez-Torrico et al. 2017; Turkyilmaz et al. 2015), such as online impulse buying. The dependent variable is important as it makes a difference whether consumers can actually choose between *different* channels or whether they are only asked about their intentions to use *one* channel. In addition, it is unclear whether personality traits have an effect when the channel is used to begin with. That is, our research aims to clarify the influence of personality traits and gender roles at an early stage of the buying process, thus as antecedents of using online purchase opportunities. Hence, our study uses a quantitative approach, assesses the channel choice as a dependent variable and uses two reliable and established inventories of personality traits (see Table 5).

Overall, we conclude that personality traits and gender roles have not been researched to a great extent in the context of channel choices and that the findings from related dependent variables and contexts are promising.

3.2.3 Hypotheses Development

Hence, we aim to extend existing research by testing the effect of personality traits on the predictors of channel choices. Therefore, we build upon the existing and established model of Kim et al. (2008) and extend it accordingly.

Replication of basic theoretical framework (hypothesis 1)

First, we replicate the basic theoretical framework of Kim et al. (2008). Therefore, we replace the purchase intention with the channel choice and we assume that the channel choice is influenced by the perceived risk, trust, and perceived benefits (Kim et al. 2008). In addition, perceived risk mediates the relationship of trust and the channel choice (Kim et al. 2008).

Hypothesis H1a: *A consumer's perceived risk negatively affects the choice of the online channel.*

Hypothesis H1b: *A consumer's perceived benefits positively affects the choice of the online channel.*

Hypothesis H1c: *A consumer's trust negatively affects the consumer's perceived risk.*

Hypothesis H1d: *A consumer's trust positively affects the choice of the online channel.*

Personality traits as antecedent of the basic theoretical framework (hypothesis 2)

The second hypothesis aims at the relationship of personality traits and the constructs of the basic theoretical framework (Kim et al. 2008). Based on previous studies (e.g. Bansal et al. 2010; Bosnjak et al. 2007), we assume that personality traits are antecedents of perceived risk, trust, and perceived benefits. However, contrary to Bansal et al. (2010), we assume that personality traits are not directed to one integrated construct (perceived health information sensitivity in their case). Instead, each trait has different relationships with the relevant constructs similar to the approach of Svendsen et al. (2013).

In particular, *neuroticism* is associated with anxiety which is illustrated exemplarily by items such as “worries a lot” or “gets nervous easily” (John and Srivastava 1999). Consequently, neurotic individuals focus on what might go wrong and tend to overlook the benefits of a new technology. Therefore, neuroticism has a positive relationship towards perceived risk and a negative relationship towards perceived benefits, such that highly neurotic participants perceive digital channels as particularly risky and less beneficial. *Extraversion* is frequently associated with being outgoing. Therefore, introverted participants value the anonymity of digital channels and shy away from social interactions. Thus, extraversion may be negatively correlated with the perceived benefits of digital channels. Nevertheless, extraverted individuals have higher trust (Tov et al. 2016; Walczuch and Lundgren 2004). *Agreeableness* is based on the assumptions of social compatibility, and of a basic trust in the goodness of people. This also influences the trust of individuals with high agreeableness and leads to a positive relationship towards trust (Walczuch and Lundgren 2004). Based on a previous study, *conscientiousness* is negatively related to perceived risk (Hampson et al. 2006). Finally, *openness to experience* antecedes trust. This hypothesis follows the argumentation that "more openness leads to more willingness to embrace new concepts and be more careless with respect to new situations and experience" (Walczuch and Lundgren 2004, p. 161).

Similar to Bosnjak et al. (2007) and given that personality traits and channel choices are under-researched, it is not possible to derive a relationship for all connections between the Big Five Inventory and perceived risk, trust, and perceived benefits. Yet, as the Big Five Inventory is usually measured with all traits, we estimate the remaining traits and relationships exploratively (Vogel et al. 2017) and report a full model in Appendix C. Overall, we hypothesize:

Hypothesis H2a: *Neuroticism negatively affects the consumer's perceived benefits.*

Hypothesis H2b: *Neuroticism positively affects the consumer's perceived risk.*

Hypothesis H2c: *Extraversion negatively affects the consumer's perceived benefits.*

Hypothesis H2d: *Extraversion positively affects the consumer's trust.*

Hypothesis H2e: *Agreeableness positively affects the consumer's trust.*

Hypothesis H2f: *Conscientiousness negatively affects the consumer's perceived risk.*

Hypothesis H2g: *Openness to experience positively affects the consumer's trust.*

Gender roles as antecedent of the basic theoretical framework (hypothesis 3)

In addition to personality traits, we suggest adding gender roles to the basic theoretical framework due to gender differences in personality traits (Giudice et al. 2012; Weisberg et al. 2011). Thereby, we assume that *femininity* has a negative influence on perceived benefits. This arises from the computer self-efficacy, which is usually lower among feminine individuals (Venkatesh and Davis 1996; Venkatesh and Morris 2000), and which impacts perceived ease of use and therefore the perceived benefits (Venkatesh and Morris 2000). When it comes to perceived risk, individuals with feminine traits are more risk-averse (e.g. Aguirre-Urreta and Marakas 2010; Inman et al. 2004) which implies a positive relationship of femininity and perceived risk. The two hypotheses are supported by the fact that participants with a high score in femininity are socialized to be help-seeking and relationship oriented (Diehl et al. 2004; Venkatesh and Morris 2000).

In turn, *masculinity*, which is related positively to self-efficacy (Venkatesh and Davis 1996; Venkatesh and Morris 2000), has a positive influence on perceived ease of use and therefore a positive relationship towards perceived benefits (Cyr et al. 2017; Venkatesh and Morris 2000). This is also supported by achievement orientation of participants with masculine traits that are usually fulfilled by the benefits of a technology (Diehl et al. 2004). Further, masculinity has a positive influence on trust as previous studies have shown for an augmented Technology Acceptance Model (e.g. Cyr et al. 2017).

Hypothesis H3a: *Femininity negatively affects the consumer's perceived benefits.*

Hypothesis H3b: *Femininity positively affects the consumer's perceived risk.*

Hypothesis H3c: *Masculinity positively affects the consumer's perceived benefits.*

Hypothesis H3d: *Masculinity positively affects the consumer's trust.*

Research model

The hypotheses are synthesized in a research model (see Figure 10 below).

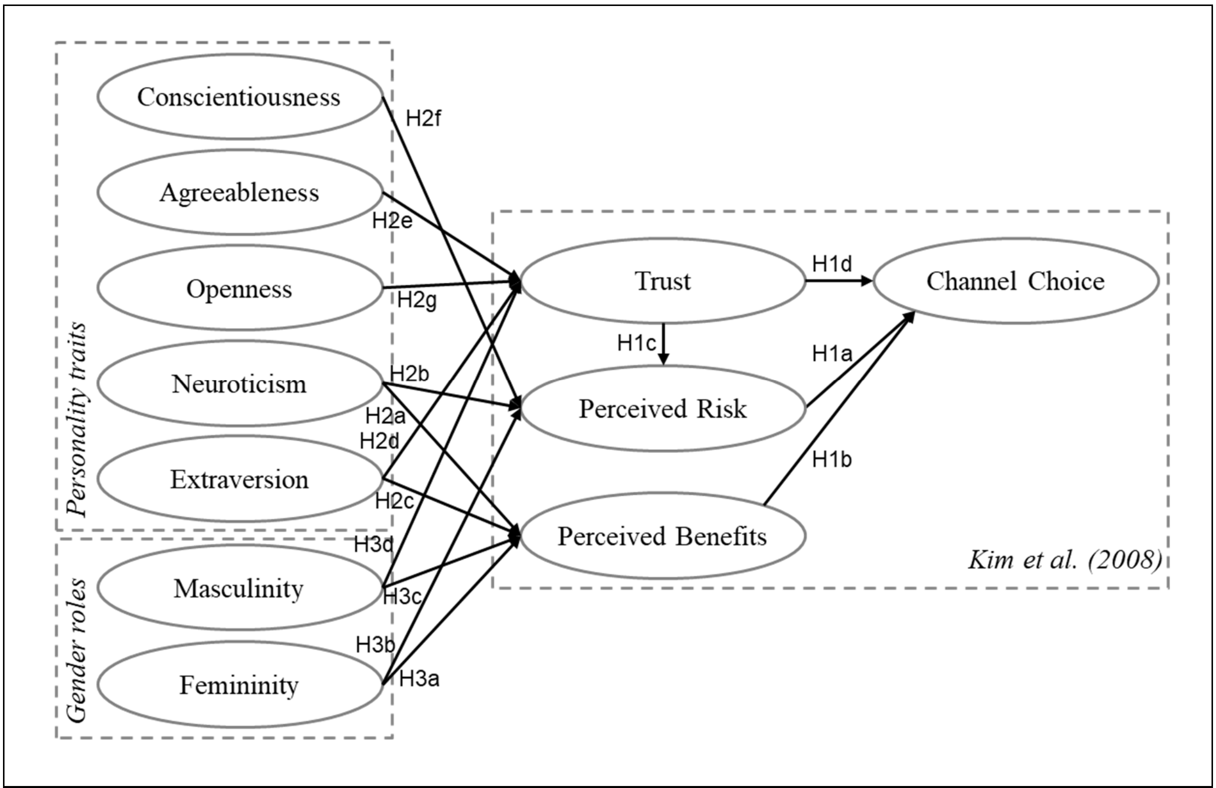

Figure 10. Research model

3.2.4 Research Methodology

Experiment design

To answer our research question, we conducted an experiment in a German university laboratory in September 2017 (Jung et al. 2018; Levitt and List 2007). Our participants were part of the lab pool which comprises mainly students of a mid-sized German city. In order to become a member of the pool, interested individuals can register themselves. The participants were invited by E-Mail to participate in the study and then could sign-up for a particular time slot. They received 8€ as a compensation for their participation. The experimental study consisted of four steps (see Figure 11).

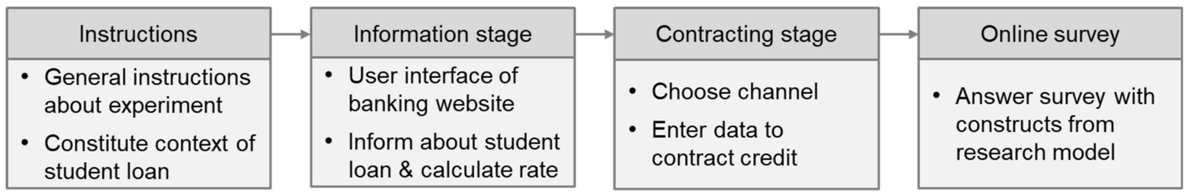

Figure 11. Experiment process

First, the participants received general information about the experiment. Thereby, they learned that the experiment covers financial decision-making in a banking context. We have chosen the financial services industry because the banking channel structures in Germany are currently being reshuffled with major branch closures and considerable investments in digital channels such as the online or mobile channel. Moreover, the financial service of student loans can be contracted online for a few years and offer a setting where the same financial service can be accessed in two different channels. Next, participants were presented general information on student loans. These pages have been inspired by the website of a large German bank, and they were important to make the experiment as realistic as possible for the participants. After informing themselves about the various financial services, in particular student loans, the participants were forwarded to an installment calculator to estimate their fictitious monthly installment rate. In the contracting phase, participants had to choose a channel to contract the loan. If having chosen the online channel, the participants had to fill out the loan form on the computer screen; if having chosen the branch, then they had to use a paper form. Finally, they completed a survey with the constructs from the research model.

Measurements

The *dependent* variable is channel choice which is operationalized as a binary choice between the online channel and the branch. As binary variables cannot measure how sure the participants were about their decision, we additionally included a confidence rating asking them how much they inclined towards their decision. Therefore, we used a seven-point Likert scale ranging from "very weak tendency towards the chosen alternative" to "very strong tendency towards the chosen alternative". The constructs of the original model, perceived risk and perceived benefits, were adapted from Kim et al. (2008). Instead of consumer trust (Kim et al. 2008), we assessed Internet trust (Dinev and Hart 2006) due to the online banking context. The personality traits are based on the Big Five Inventory using the 42-item questionnaire (John and Srivastava 1999; Lang et al. 2001). Moreover, we measured the Bem Sex Role Inventory (Bem 1974) using the 20-item questionnaire (Hunt et al. 2007) with the German items from Sieverding (2009). All items were measured using a seven-point Likert scale. The German and English measurement items can be found in Appendix B. As a quality check, we measured further constructs to assess their influence as an alternative explanation for the channel choice. These constructs were personal Internet interest (Dinev and Hart 2006), process digitizability (Graupner and Maedche 2015), web shopping risk attitude (Everard and Galletta 2006), information insecurity (new items), and online banking usage (Fang et al. 2006). Again, all items, except for online banking usage, were measured using a seven-point Likert scale. Moreover, we asked for age, gender, education, Internet usage, whether and where they contracted a loan in the past, as well as their reasons for the channel choice (open text field). Finally, we included open questions on what factors influenced the channel choice. The survey was conducted in German so that some items were forward and backward translated.

Several pre-tests of the experiment prototype and the survey were conducted prior to the actual experiment. In February 2017, four employees of a large German bank examined the experiment using the think-aloud technique. Results confirmed the representativeness of the experiment design for the banking sector and revealed only minor spelling mistakes. In a second pre-test, 30 participants from the lab pool were invited to take part in the study two weeks prior to the large-scale data collection. The participants were not informed that they were part of a pre-test and that their data would not be used to answer the research question. This pre-test revealed technical feasibility and was used to estimate the time length of the experiment.

Data analysis

We used Structural Equation Modelling (SEM) to derive the path estimates. Generally, SEM can be divided into the covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) which are variance-based (Hair et al. 2011, 2017). In this study, we used a covariance-based approach. Covariance-based approaches offer a variety of goodness-of-fit indicators and they provide a more reliable evidence for the fit between the theoretical model and the observed empirical data (Hair et al. 1998, 2017). Moreover, CB-SEM is primarily used for confirmatory research objectives (Hair et al. 2017). To do so, we modelled the research model with IBM SPSS Amos 23.0.0 using a maximum likelihood estimation. With a sample size of 236 participants, the experimental study exceeds the threshold of 100, which is suggested for the maximum likelihood estimation in structural equation modelling (Hair et al. 1998). We follow the general recommendation that the data analysis should comprise the evaluation of the measurement model and the structural model (Anderson and Gerbing 1988; Hair et al. 2011). We used z-scores for the independent variables which yields a consistent threshold value for statistical significance in the statistical model.

3.2.5 RESULTS

Descriptive analysis

Overall, 244 participants took part in the laboratory experiment. Eight participants had to be excluded as they failed to answer two test items correctly, or as they showed insufficient language skills in the open text fields. On average, it took the participants about 35 minutes to complete the study. Demographical data of the remaining 236 participants (see Table 6) showed an age ranging from 16 to 50 years with an average of 24 years. They used the Internet on average 4.8 hours per day, and only few participants (12.3%) had contracted a loan before. Hence pre-knowledge is not a concern. In sum, our sample was more male, younger and higher educated than the average German Internet population (Statista 2018). This distribution was expected, as the participant pool is dominated by students of the local technical university. Yet, also the original study (Kim et al. 2008) has a similar age structure and gender distribution with an average age of 22 years and 58% male participants. In order to replicate and extend their study, we needed a comparable sample. Moreover, several banks in Germany have announced to target the younger generation with a high affinity towards digital channels which supports using a younger sample. Therefore, we consider our sample to be appropriate.

Table 6. Demographics of laboratory experiment participants

Attribute	**Characteristic**	**Total**	**%**
Gender	Male	139	58.9%
	Female	97	41.1%
Age	16-24	155	65.7%
	25-30	75	31.8%
	>30	6	2.5%
Highest degree	A-levels (“Abitur”)	111	47.0%
	Bachelor	99	41.9%
	Master	10	4.2%
	Other	16	6.8%
Contracted loan before	Yes	29	12.3%
	No	207	87.7%

Concerning the channel choices in the experiment, 114 participants (48%) chose the branch, while 122 (52%) participants decided to contract the student loan via the online channel. Based on the open text field, we gained insights into the reasons for the channel choices. The online channel was mainly chosen because of its convenience, speed of closing the transaction and due to unpleasant experiences in a banking branch. On the other hand, the branch was chosen because of insufficient product knowledge, riskiness of the online channel and the possibility to clarify open questions. This is in line with previous research (Black et al. 2002; Hoehle et al. 2012).

Measurement model, construct reliability and validity

First, the measurement model assessed the reliability, convergent validity as well as the discriminant validity of the relevant constructs in the main study (Straub 1989). Therefore, Cronbach's alpha (Cb. α), the composite reliability (CR), and the average variance extracted (AVE) were estimated. In addition, we present the mean and the standard deviation (SD) of each construct.

Table 7. Measurement model assessment and descriptive statistics

Variable	Construct	Abbr.	Cb. α	CR	AVE	Mean	SD
Personality traits	Extraversion	EXT	0.89	0.89	0.51	4.73	1.05
	Agreeableness	AGR	0.64	0.73	0.26	4.72	0.73
	Conscientiousness	CON	0.71	0.31	0.14	4.77	0.77
	Neuroticism	NEU	0.85	0.89	0.53	3.64	1.08
	Openness	OPE	0.72	0.56	0.21	4.84	0.71
Gender roles	Masculinity	MAS	0.88	0.89	0.46	4.72	0.87
	Femininity	FEM	0.89	0.91	0.51	4.88	0.88
Variables original model	Perceived Risk	RIS	0.72	0.84	0.64	3.56	1.21
	Trust	TRU	0.70	0.83	0.62	3.91	1.04
	Perceived Benefits	BEN	0.79	0.88	0.71	5.80	1.03

Note: Abbr. = Abbreviation; Cb. α = Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted; SD = Standard deviation

For Cronbach's alpha, all constructs, except for agreeableness, meet the recommended threshold of 0.70 (Bearden et al. 1993). Concerning the composite reliability, all constructs, apart from conscientiousness and openness, meet the established cut-off value of 0.70 (Nunnally and Bernstein 1994). Moreover, we calculated the AVE values for each construct as the AVE can be used to estimate the discriminant validity. The AVE values should exceed the threshold of 0.5 (Fornell and Larcker 1981) which is the case for all constructs except for agreeableness, conscientiousness, openness and masculinity. Thereby, masculinity is only slightly below the threshold. The implications of the reliability measures will be discussed in the next chapter. The mean values for the personality traits of the Big Five Inventory are similar to other studies in Germany (Lang et al. 2001). Compared with the original study (Kim et al. 2008), our sample perceived less risk, had less trust, but perceived slightly higher benefits.

In addition, we set up a correlation matrix to be able to compare the inter-construct correlation and the square root of the AVE (Fornell and Larcker 1981) (see Table 8). The values for the AVE values should exceed the inter-construct correlations for adequate discriminant validity (Chin 1998; Fornell and Larcker 1981; Kim et al. 2008). Note that not all square roots of the AVE exceed the inter-construct correlations, in particular not for openness and conscientiousness. Again, the implications will be discussed in the next chapter. Overall, the results indicate that the measurement model is appropriate for the research model except for conscientiousness and openness as these constructs fail to meet several criteria. We also estimated the variance inflation factors (VIFs) to control for threats of multicollinearity. However, all VIFs ranged between 1.0 and 1.9, and they were thus below the recommended cutoff value of 5 (Hair et al. 2011).

Table 8. Inter-construct correlation matrix

	EXT	AGR	CON	NEU	OPE	MAS	FEM	RIS	BEN	TRU
EXT	**0.71**									
AGR	0.25	**0.51**								
CON	0.28	0.29	**0.37**							
NEU	-0.37	-0.21	-0.25	**0.73**						
OPE	0.31	0.17	0.37	-0.18	**0.46**					
MAS	0.65	-0.00	0.35	-0.42	0.38	**0.68**				
FEM	0.25	0.57	0.37	0.01	0.32	0.19	**0.71**			
RIS	-0.06	0.02	-0.03	0.07	0.04	-0.01	0.15	**0.80**		
BEN	0.03	0.04	0.06	-0.25	0.10	0.18	-0.02	-0.16	**0.84**	
TRU	0.04	0.10	-0.03	-0.15	0.02	0.10	0.02	-0.20	0.29	**0.79**
CHO	0.01	-0.04	0.04	-0.17	-0.01	0.14	-0.15	-0.33	0.42	0.34

Note: Square root of AVE shown in bold; CHO = Choice

As can be retrieved from the Table 8 (lower row), the channel choice showed the strongest correlations with perceived risk, perceived benefits and trust which are all constructs from the basic theoretical framework (Kim et al. 2008). However, it also shows significant zero-order correlations with neuroticism, femininity and masculinity. This provides initial support for the predictive value of personality traits and gender roles.

Structural model assessment

Next, following the recommendations of a two-step approach (Anderson and Gerbing 1988), we estimated the structural model. The structural model includes the standardized regression weights for the estimated path coefficients of the model (see Figure 12).

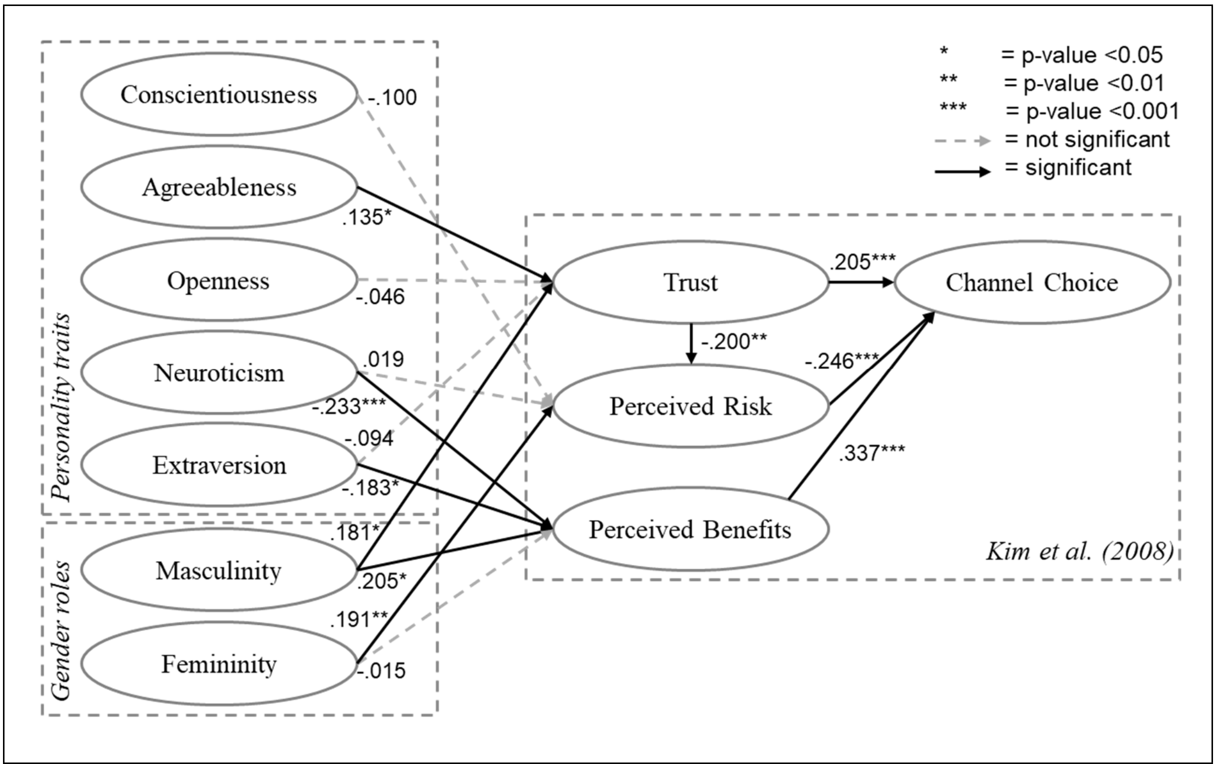

Figure 12. Results of the structural model

The structural model shows that the basic theoretical framework has significant effects between trust, perceived risk, perceived benefits and channel choice. In particular, trust has a strong negative relationship towards perceived risk while it has a positive relationship towards channel choice. Also, as expected, perceived benefits have a strong positive relationship towards channel choice. The effects even have a similar strength compared with Kim et al. (2008), and therefore, hypotheses H1a to H1d are supported.

Next, we turn to the results of the Big Five Inventory. Thereby, *neuroticism* had indeed a strong negative effect on perceived benefits, thus supporting H2a. However, neuroticism did not have a significant positive effect on perceived risk. Hence, H2b is not supported. Similarly, *extraversion* was expected to negatively affect perceived benefits. The data supports this relationship and thus also H2c is supported. Yet, extraversion shows no significant negative effects on trust. Consequently, H2d is not supported. In turn, *agreeableness* had a strong positive effect on trust, thus supporting H2e. For the remaining two traits, *openness* and *conscientiousness*, we could not find any significant paths. So overall, hypotheses H2a, H2c and H2e are supported, while hypotheses H2b, H2d, H2f, and H2g are not supported.

Finally, we turn to the Bem Sex Role Inventory. The relationship of *masculinity* and trust as well as of masculinity and perceived benefits is positive and significant. Thus, hypotheses H3c and H3d are supported. In addition, we predicted a positive relationship of *femininity* and perceived risk. The data supports this relationship and hence H3b is supported, too. Only the relationship of femininity and perceived benefits is insignificant. So overall, hypothesis H3a is not supported but hypotheses H3b to H3d are supported.

In sum, we conclude that especially perceived benefits and trust are significantly anteceded by several personality traits and gender roles. This conclusion still holds true when the model is calculated with all possible combinations between the personality traits and gender roles on the one hand, and perceived risk, perceived benefits and trust on the other hand (see Appendix C).

Finally, we report further results on channel choices using control variables. We could only find marginal differences in the results when controlling for demographics. Thereby, the results do not differ significantly in terms of age, gender, or education. Interestingly, those participants that have chosen the branch, report a slightly higher Internet usage which is counterintuitive compared with previous research (McGoldrick and Collins 2007; Park and Jun 2003).

3.2.6 Discussion

Our aim was to investigate the influence of personality traits and gender roles in the context of channel choices, and to incorporate them in an existing decision-making model. Overall, certain personality traits and gender roles antecede the constructs of the original model. The results can be discussed in three ways.

First, the *personality traits* show an effect on trust and perceived benefits. Naturally, *neuroticism* negatively affects online channel choices. Thereby, neurotic participants are anxious, focus on the negative aspects, and disvalue the benefits of the online channel. In line with our prediction, neurotic people were less likely to choose the online channel (Table 8). The results of the SEM indicate that this effect is explained by the negative relationship with the perceived benefits of the online channel. Surprisingly, neuroticism did not correlate with perceived risk (also Table 8), nor was this path significant in the SEM (Figure 12). For *extraversion*, we expected a negative relationship towards perceived benefits, and the data supports this relationship. An explanation for this result might be that introverted consumers specifically value the anonymity of the online channel. We offer an alternative explanation that the items for perceived benefits focus on saving time and convenience (Kim et al. 2008) while extravert individuals are energetic, active and sociable (John and Srivastava 1999; McCrae and John 1992). Hence, there might be a misfit between convenience and the energy/activity. Complementing this explanation, Turkyilmaz et al. (2015) found a positive effect of extraversion on online impulse buying. Yet, other studies (Bansal et al. 2010; Walczuch and Lundgren 2004) found no effect at all. Thus, more research will be needed to clarify the process by which extraversion affects channel choices. In turn, we find no effect for extraversion and trust. The lacking correlation between the two constructs is in line with a previous study (Walczuch and Lundgren 2004). *Agreeableness* is the trait complies most with our hypotheses. As agreeableness is positively related to trust, we trace this back to the social compatibility and the basic trust in the goodness of people. This is also in line with the finding that participants with high agreeableness also rated the provider of the online channel as slightly more trustworthy (without knowing anything about our fictitious bank). Again, as far as this can be compared, this is in contrast to Bansal et al. (2010), and it might either be attributable to the context of health vs. financial services, or that Bansal et al. (2010) directed all personality traits towards one construct (perceived health information sensitivity), and not towards the antecedents of the dependent variable. Finally, no significant relationships, and no correlation with the dependent variable could be found for *conscientiousness* and *openness to experience*. Although this is in line with Walczuch and Lundgren (2004), it would be premature to refuse that conscientiousness and openness to experience affect the channel choice. The lack of results in the SEM could reflect the poor reliability of these measures. Overall, the validity of conscientiousness and openness to experience cannot be discussed appropriately as the reliability is too low.

Moreover, another study found significant effects for all Big Five personality traits when measuring their effect on online impulse buying behavior (Turkyilmaz et al. 2015). Based on our correlation matrix, we see that only neuroticism decreases online channel choice. This might again be due to reasons of reliability, or this result can be traced back to the insecurity of conducting banking services online. Frequently in the past, major German banks reported bugs or security issues related to the online banking which might be considered as more severe by neurotic individuals. Yet, we could not find any significant effects for the other traits of the Big Five Inventory, which also lacked a correlation with the dependent variable (see Table 8).

Secondly, also *gender roles* seem to play an important role in channel choices. Except for the relationship of femininity and trust, all relations are significant. To explain these results, we use the gender schema theory (Bem 1981) which states that societal beliefs lead to the creation of gender schema at younger ages of individuals. Once established, these gender schemas influence the processing of information and also influences the self-esteem which leads to a behavior that is consistent with the gender schema (Bem 1981). Hence, masculine and feminine individuals might have created gender schemas towards what is expected of their gender role in terms of risk-aversion and trust. This leads to their positive/negative association with the predictors of channel choices. Notably, these effects occurred though there were no direct or moderating effects of biological sex, demonstrating the prime relevance of psychological inter-individual differences for understanding channel choices.

Third and finally, we were also able to *replicate* the original basic theoretical framework of Kim et al. (2008) in an experimental context with similar effect sizes. This is important as it has been frequently noticed that replications fail or lead to entirely different results (Erdfelder 2018). Thereby, our replication in an experimental setting with a financial services context strengthens the empirical base of the basic theoretical framework.

3.2.7 Conclusion

To conclude, this study makes several theoretical and practical contributions. Theoretically, the main finding is the extension of the basic theoretical framework of Kim et al. (2008) with personality traits and gender roles. These personality traits and gender roles involve especially neuroticism, extraversion, agreeableness, masculinity, and femininity. The study highlights in particular that it is not sufficient to design an information system autarkically, but that the individual characteristics of the prospective users always have to be taken into account. In addition, we were also able to replicate the original model (Kim et al. 2008) in an experimental context.

Practitioners are a core target group of IS research (Te'eni et al. 2017). Therefore, especially in financial services companies, they benefit from our work by deriving insights for the design of their channels (Chau 2002). Our study provides the basis for matching individual characteristics with channel characteristics. Thereby, the benefits of the digital channel, e.g. broad product spectrum or convenience, should be highlighted particularly to introverted consumers or consumers with low neuroticism. In addition, consumers with feminine traits could be reached with risk-reducing messages, privacy and security seals (e.g. Bansal et al. 2015; Mousavizadeh et al. 2016) or other IS artefacts (Lowry et al. 2017). Alternatively, participants with high masculinity have trust in the online channel and they are inclined towards the benefits of it. This can be exploited in similar ways as for introverted consumers and consumers with low neuroticism.

Our study also has societal implications. As more and more (banking) branches are closed, certain personality traits are systematically excluded from technology-based purchasing opportunities as they avoid using digital channels. This effect is even supported by the suggestions we made for practitioners to individualize their digital channels to a particular set of personality traits. From an equality perspective, it would be beneficial to outweigh the disparities in channel choices. This can only be solved by investing in capabilities, such as security features, that attract online-distant personality traits and gender roles. Moreover, consumers themselves could save time and reduce information overload by using individualized digital channels. Hence, even infinitesimal time-savings of reduced purchasing processes add up to large time-savings in a society.

A limitation of this study is the somewhat artificial setup of a laboratory experiment. As no financial assets were at stake, the participants might not have felt the anxiety and pressure of contracting a real student loan. We tried to tackle this problem by developing a complex website structure, by urging them to behave as if real money was involved, and by leaving them in the dark about the intention of the study. In addition, the sample is younger and includes more students than the Internet population of Germany (Statista 2018), but which is in line with the original study (Kim et al. 2008). As we aimed mainly for inter-individual differences unrelated to age, this limitation is of minor relevance. Moreover, two personality traits, conscientiousness and openness to experience, perform poorly in terms of reliability and no conclusions can be drawn for the BFI as a whole.

Future research could test whether personality traits and channel preferences can be compensated by building dedicated decision support systems (DSS). Therefore, textual or visual decisional guidance (Morana et al. 2017) could be implemented using seals or digital nudges (Weinmann et al. 2016). This would enable the providers of digital channels to influence consumer decisions regardless of the personality traits. Moreover, the decision support could be implemented adaptively by first assessing the characteristics and preferences of the consumer, and then be adapted in real-time to match them. It might also be interesting to use a more representative sample in terms of age and technology affinity, or to replicate our experiment using a different product, service or context. Finally, the personality trait of extraversion has produced contradicting results and more research is needed to clarify its role in online environments.

3.3 Intermediate Summary and Discussion

The results of Chapter 3 show that multi-channel behavior has a variety of determinants, which can be clustered into four dimensions: channel, context, consumer and product. Thereby, constructs, such as a low perceived risk, high perceived benefits, an immediate availability, or a high trust support the choice of digital channels. The morphological box now allows for a consistent classification and comparison of the determinants of multi-channel behavior across different studies. Such a comprehensive conceptualization was not provided by earlier studies (Neslin et al. 2006; Trenz and Veit 2015) and can be used by researchers and practitioners.

Building on these findings, the second part of Chapter 3 was based on an existing model (Kim et al. 2008), and it has shown the interconnections of individual characteristics and channel characteristics. Thereby, it finds that personality traits and gender roles antecede the constructs of perceived risk, trust and perceived benefits. The findings can be used for an individualization of digital channels.

It can be concluded from Chapter 3 that not only the characteristics of digital channels matter but also the individual consumer characteristics. However, these findings leave few possibilities for providers of digital channels to actively influence consumer behavior in digital channels. This can be achieved using the concept of "nudging" (Thaler and Sunstein 2008) and "digital nudging" (Weinmann et al. 2016) which is the focus of Chapter 4.

4 Nudging Consumer Choices in Digital Retail Channels

4.1 Study 3: How Effective is Nudging? A Quantitative Literature Review[3]

4.1.1 INTRODUCTION

Behavioral economics, in contrast to traditional economics, has nuanced our way of interpreting human behavior. Nudging is one particular area of behavioral economics (Thaler and Sunstein 2008; The Royal Swedish Academy of Sciences 2017). By definition, nudges are "any aspects of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein 2008, p. 6). Since the origin of the concept in 2008, governments in the US, UK, Germany and many more have implemented departments of behavioral economics (e.g. Behavioral Insights Team 2016; Social and Behavioral Sciences Team 2016). Therefore, nudges are not just a theoretical concept anymore, but now affect citizens in many countries through its influence in the political decision-making process.

Yet, it remains unclear if nudges really work and, if so, under which conditions. For example, the Science and Technology Committee of the United Kingdom, overseeing the Behavioral Intervention Team, has raised doubts whether experiments can be supported by appropriate evidence (see Halpern 2016; Kosters and Van der Heijden 2015). Also recent studies indicate limited influences of nudging (D'Adda et al. 2017; Esposito et al. 2017), or even report backfire effects with unintended consequences (e.g. Liu et al. 2016; See et al. 2013). For example, policy makers could choose defaults in the wrong environment which harms decision-makers by opting out in the wrong moment (Willis 2013). Moreover, one of the authors of the nudging concept has even dedicated a separate journal paper on "nudges that fail" (Sunstein 2017). Systematic reviews are a common and appropriate method in (behavioral) economics to clarify such questions (e.g. Lane 2017).

Qualitative and quantitative systematic literature reviews have been conducted on the topic of nudging before (e.g. Benartzi et al. 2017; Lycett et al. 2017; Wilson et al. 2016). Yet, these studies are mostly limited to a certain context, for example the health context (e.g. Adam and Jensen 2016; Bucher et al. 2016), or they are too narrow with as little as 18 studies (Benartzi et al. 2017). Therefore, it is questionable whether today's results on nudging are generalizable. We assume that existing research is not suited to provide an answer to the challenge of failing nudges described above. In this study, we clarify the effects and limits of nudging by means of a quantitative literature review.

[3] This section is based on Hummel and Maedche (2018)

Nudging, and the question of its effectiveness, is also becoming increasingly important in the digital age due to a more frequent decision-making in digital environments. This raises the relevance of research on digital nudging. Digital nudging is "the use of user-interface design elements to guide people's behavior in digital choice environments" (Schneider et al. 2018; Weinmann et al. 2016). Although some research on the topic of digital nudging is already conducted (Gregor and Lee-Archer 2016; Hummel et al. 2017a; Pahuja and Tan 2017), it remains unclear what can (not) be transferred from the study of offline nudges. Thus, we aim to answer the following research question:

Research Question*: How can nudges be classified and what are the influencing factors for the effectiveness of different nudge treatments?*

In order to answer the research question, we conducted a systematic literature review across the disciplines of psychology, economics and information systems following the guidelines of systematic literature reviews (e.g. vom Brocke et al. 2009). Moreover, our study goes one step further by not only gathering and synthesizing the literature, but also by conducting a quantitative analysis (Kitchenham 2004; Stanley 2001) on the effect sizes of nudges. By covering 100 studies including 319 effect sizes, we claim to provide a cross-discipline and a cross-contextual analysis of nudging.

Thereby, this study contributes to existing research in four ways: (1) we create a morphological box on empirical nudging studies with eight dimensions, (2) we assess the overall effectiveness of the nudging concept with a median effect size of 21%, (3) we define the relative importance of context, nudge category, and other factors for the effectiveness of nudging, and (4) we provide avenues for future research in digital nudging. These contributions are particularly helpful as tools of behavioral economics are gaining increasing popularity in various research disciplines, and as a comprehensive and holistic overview is likely to accelerate these research activities. We also provide implications for practitioners. Especially government officials, that are responsible for nudging activities in policy making, can use our results to improve policy making in various fields.

This study is organized as follows. Chapter 4.1.2 defines behavioral economics and nudging, outlines the related work on nudging, and derives the research gap. Next, the methodology of the systematic literature review and the quantitative analysis are described (Chapter 4.1.3). In Chapter 4.1.4, we document the results of the literature review in the form of a morphological box, and we conduct the quantitative analysis of the effect sizes. Chapter 4.1.5 discusses the results and compares them with existing research. Finally, Chapter 4.1.6 highlights future research and the limitations of this study.

4.1.2 Theoretical Background

Nudging and digital nudging

While neoclassical economics assumes decision-makers to always make rational choices that incorporate all available information, behavioral economics has integrated knowledge from psychology to illustrate the boundaries of rational decision-makers (Camerer and Loewenstein 2004; Kahneman 2011). Behavioral economics traces back to the work of Adam Smith in the 18th century (Camerer and Loewenstein 2004), but has received greater attention with the research of Tversky and Kahneman (e.g. Tversky and Kahneman 1973, 1981), especially on their advancement of the dual process theory (Kahneman 2003). For instance, they found that the framing of a decision influences the outcome (Tversky and Kahneman 1981), or that the ease of recalling a particular piece of information determines the expected probability of its occurrence (Tversky and Kahneman 1973).

The concept of nudging is based on behavioral economics and the dual process theory. It assumes that the choice architecture can be used to alter people's behavior (Thaler and Sunstein 2008). For example, assuming that individuals are willing to donate their organs unless they declare otherwise (i.e. setting the default to an opt-out mechanism), dramatically increases the percentage of organ donors (Johnson and Goldstein 2003; Thaler and Sunstein 2008). By today, nudging is a widely applied concept by researchers and practitioners. Researchers used it to conduct experiments in different contexts to improve decision-making (e.g. Costa and Kahn 2011; Kallbekken and Sælen 2013; Luoto et al. 2014). A typical study starts with a real world behavioral problem, e.g. few people make check-up appointments with the dentist (Altmann and Traxler 2014). Then the typical study identifies suitable nudges to resolve the issue. In the dentist example, different (postal) reminders were sent out to patients. Thereby, a treatment group receives a nudge with a happy or sad face while the control group only receives a neutral reminder (Altmann and Traxler 2014). The results are evaluated in comparison with a control group to derive implications for researchers and practitioners (see also the nudging cycle of Schneider et al. 2018).

In 2016, the concept of nudging has evolved to the digital sphere called "digital nudging" (see definition above). Currently, there is a growing stream of conceptual papers on digital nudging. These papers encompass literature reviews (Mirsch et al. 2017), research-in-progress papers, mainly on experimental designs or with preliminary results (Djurica and Figl 2017; Székely et al. 2016), or policy papers (Gregor and Lee-Archer 2016). Although the term "digital nudging" was only introduced in 2016, researchers have used changes in the user interface before (e.g. Almuhimedi et al. 2015; Demarque et al. 2015). As numerous studies using nudges have already been conducted, nudging has been examined in various literature reviews in the past.

Literature reviews nudging

Based on a non-systematic literature search, we identified 11 literature reviews and quantitative analyses that have already been conducted on the topic of nudging (see Table 9). Most of these literature reviews focus on the context of health. For instance, Bucher et al. (2016) review the positional influence on food choices and find that the manipulation of food product order or the proximity can influence food choices. Lycett et al. (2017) review nudging strategies for dietary behavior of children while Cadario and Chandon (2017) conduct a meta-analysis (MA) on eating behavior interventions. These literature reviews and meta-analyses are summarized in Table 9.

Table 9. Overview of existing literature reviews and meta-analyses on nudging

Reference	**Context**	**Main variable**	**#Papers**	**Method**	**Exemplary results**
Abrahamse et al. (2005)	Energy	Household energy conservation	38	SLR	Information results in higher knowledge levels, but not necessarily in behavioral change or saving energy
Skov et al. (2013)	Health	Eating behavior in self-service settings	12	SLR	Labelling, plate and cutlery size, assortment and other manipulations are associated with healthier food choices
Arno and Thomas (2016)	Health	Adult dietary behavior	37	SLR and MA	Nudges resulted in average 15.3 % increase in healthier dietary or nutritional choices
Lehner et al. (2016)	Environment	Sustainable consumption behavior	n/a	SLR	Size of the effects of policy interventions and outcomes in different contexts are very diverse
Adam and Jensen (2016)	Health	Obesity related interventions at supermarkets	42	SLR	Most studies reported that store interventions were effective in promoting purchase of healthy food
Bucher et al. (2016)	Health	Positional influences	15	SLR	Manipulating food product order and proximity can influence food choice
Wilson et al. (2016)	Health	Healthy food and beverage choices	13	SLR	Mixed effectiveness of nudging in healthier food and beverage choices
Mirsch et al. (2017)	Digital	Digital nudging	65	SLR	Psychological mechanisms that underlie digital nudging

Lycett et al. (2017)	Health and education	Children's dietary behaviors	40	SLR	Studies showed improvement in dietary behaviors and were more effective for older children
Cadario and Chandon (2017)	Health	Healthy eating nudges	78	MA	Experiments yields a moderate but significant overall effect size (d=.28)
Benartzi et al. (2017)	Cross-context	Nudging and traditional policy tools	18	QA	Nudges often compare favorably with traditional interventions
This study	Cross-context	Overall effect sizes of nudging	100	SLR and QA	See below
SLR = Systematic literature review; MA = Meta-analysis; QA = Quantitative analysis					

The overview shows that existing literature reviews have been limited to a certain context, such as health. Hence, specific conclusions can only be drawn for this context, but they do not allow for a generalized view on nudging nor for a cross-context comparison. However, the context is important, as it is assumed that the effectiveness of nudges might depend on it (see Kosters and Van der Heijden 2015). In addition, the evidence is limited as most literature reviews used far less than 100 studies.

When it comes to quantitative or meta-analyses, three studies were identified. Kosters and Van der Heijden (2015) approached the effectiveness of nudges across different disciplines. Yet, they did not perform it in a systematic manner and they included too few studies (17 studies from 13 different sources) to be able to generalize the results. A similar conclusion can be drawn for Benartzi et al. (2017) which conducted a review and compared the relative effect sizes of nudges and traditional interventions. Thereby, the authors conclude that nudges often compare favorably with traditional interventions, but they only included 18 studies in total (Benartzi et al. 2017).

In sum, we identified a research gap to provide a holistic evaluation of the effectiveness of the nudging concept and a classification of different types and categories of nudges.

4.1.3 Research Methodology

Systematic literature review

In order to answer the research question, we conducted a systematic literature review following the suggestions of vom Brocke et al. (2009). The approach consists of five steps: definition of review scope, conceptualization of topic, literature search, literature analysis and synthesis, and research agenda (vom Brocke et al. 2009). The definition of the review scope and the conceptualization of the topic have been presented in the introduction. Therefore, we focus now on the actual literature search. We used the keywords of "nudge" OR "nudging" in three databases (see Table 10).

Based on the hits, we implemented several exclusion criteria. We did not include studies before 2008, as the term nudging, which is central in our keywords, barely existed before the work of Thaler and Sunstein (2008). We also did not include studies from 2018 as the literature search was conducted in early 2018. Moreover, we did not include studies that did not mention, “nudge” or “nudging”, that did not quote the original work (Thaler and Sunstein 2008), or that had no other link to the nudge concept. On the one hand, this ensured the comparability of the identified studies as they all comply with the same concept. On the other hand, we might omit studies that used nudge-like interventions but did not label them accordingly (e.g. Halpern et al. 2013; Karlan et al. 2016). This ambivalence will be addressed in the discussion. Moreover, we excluded studies that were not using nudges as a concept to influence human behavior, such as *Improvement of morphodynamic modeling of tidal channel migration by nudging* (Chu et al. 2013). We also excluded policy papers that discuss nudging from an ethical or a policy perspective (e.g. Selinger and Whyte 2011), as all included papers had to show measurable effects of their intervention. Most importantly, we also excluded studies that labelled their intervention as a “nudge”, but which failed to meet the nudging definition. As an example, some studies used financial incentives (Riggs 2017), but still labelled their approach a “nudge”.

Table 10 shows the narrow down from hits to selected studies when the exclusion criteria were applied. The terms nudge OR nudging were searched for in the title, abstract or keywords of the studies. Thereby, we generated almost 2,500 hits and were able to screen out about 1,300 papers based on the title or the journal. This number is so large because of many studies from natural sciences (see example in italics above) where the word “nudge” is frequent but has a different meaning. Therefore, we reviewed the abstract or screened the document of the remaining 1,146 papers. Most papers used the term nudging correctly but conducted only qualitative studies without effect sizes. Especially in law and political sciences, nudging is a well-covered topic (e.g. Alemanno and Spina 2014; Strahilevitz and Porat 2014), but without empirical studies. This led to the perusal and review of 280 full texts. At this point, most papers used the correct concept in an empirical setting, but it had to be checked in detail if the treatment is in line with the definition of nudges. After removing such papers, we were left with 79 studies from the initial search. We identified another 21 studies through forward and backward search. Thus, the final literature review consists of 100 studies.

Table 10. Search string, databases and narrow-down of systematic literature review					
Database	**Keywords**	**No. of hits**	**No. of papers with abstract reviews and document screening**	**No. of full text reviews**	**No. of papers used for SLR**
ScienceDirect	Nudge OR Nudging	549	366	94	32
EBSCOHost	Nudge OR Nudging	1,929	765	173	45
AISeL	Nudge OR Nudging	15	15	13	2
Sum database searches		2,493	1,146	280	79
Forward and backward search					21
Total articles included					**100**

Coding

We extracted different information from the primary studies. Firstly, we excerpted general information such as authors, title, keywords or the name of the journal. Then, we identified year, context, country and the dependent variable of the study. Next, we looked for the nudge category, the absolute and relative effect size, the significance, the number of participants, the number of studies, the data collection method, and whether the nudge occurred in a digital environment (see Table 11). All data was systematically stored in a spreadsheet and analyzed accordingly.

Table 11. Exemplary extract of data storage									
#	**Source**	**Country**	**Context**	**Category**	**Effect**	**P value**	**Data**	**…**	**Digital**
1	Allcott (2009)	USA	Energy	Social norm	1.95%	0.01	Field experiment	…	No
2	Almuhimedi et al. (2015)	USA	Privacy	Disclosure	35.3%	n/a	Field experiment	…	Yes
3a	Bartke et al. (2017)	Germany	Finances	Social norm	27.1%	0.089	Field experiment	…	No
3b	Bartke et al. (2017)	Germany	Finances	Social norm	62.5%	0.001	Field experiment	…	No
…		…	…	…	…	…	…	…	…
100	Loeb et al. (2017)	USA	Health	Default	444%	0.001	Lab experiment	…	No
Note: Bartke et al. (2017) appears twice as they employed two types of treatments (descriptive norms and guessing the norm) which are both coded as "social norms"									

We define the absolute effect size as the difference between the value of the dependent variable of the treatment group and the control group. Therefore, the absolute effect size can be both a numerical value and a percentage value. More important is the relative effect size. The relative effect size is defined as the percentage change between the dependent variable of the treatment group and the control group. It is important to extract relative effect sizes (similar to Benartzi et al. 2017), as the dependent variables of the different studies are very diverse, and otherwise hard to compare. The use of absolute and relative effect sizes as measures of effectiveness is also supported by other publications (Benartzi et al. 2017; Halpern 2016). Beyond the relative effect size, we do not use other measures, such as Cohen's d (Cohen 1988) as the standard deviation or variance, which is needed for the calculation of Cohen's d, was not reported in all studies.

Development of morphological box

Upon identifying relevant papers, we built the morphological box following the suggestions for taxonomy development (Nickerson et al. 2013). Thereby, we followed the intuitive approach of Nickerson et al. (2013). Although not being as systematic as the inductive or deductive approach, the intuitive approach is the most common one (see Table 1 in Nickerson et al. 2013). Chapter 4.1.4 provides the reasoning for each dimension and each characteristic of the morphological box. We deliberately decided to generate a morphological box rather than a taxonomy as the characteristics in each dimension, for example clusters of outcomes, are not always mutually exclusive and collectively exhaustive (Nickerson et al. 2013).

Quantitative analysis

Beyond integrating existing knowledge of nudging, we also perform a quantitative analysis of the effectiveness of nudges. In the beginning, we aimed for a meta-analysis (e.g. Gurevitch et al. 2018). Yet, missing standard deviations and other measures of some studies included in the systematic literature review prevented us from fulfilling the high requirements of meta-analyses (Gurevitch et al. 2018). Hence, we followed established suggestions of conducting quantitative literature reviews (Kitchenham 2004; Pickering and Byrne 2014; Ressing et al. 2009; Stanley 2001), also labelled quantitative analysis (Okoli and Schabram 2010; Prat et al. 2015). Similar to meta-analyses, quantitative literature reviews provide an overview of the state of research on a given topic (Pickering and Byrne 2014) with a focus on quantitative outcomes such as odds ratios or mean differences (Kitchenham 2004). Quantitative literature reviews have similar limitations as meta-analyses: publication bias, research bias, incomplete data reporting in primary publications, or the quality of studies (Gurevitch et al. 2018). We will account for these concerns in the discussion and the limitations. To conduct the quantitative analysis, particularly the effect sizes, the sample sizes, the p-values as well as the context and the nudge category are extracted from the primary publications.

4.1.4 RESULTS LITERATURE REVIEW

Results morphological box

First, the results of the literature review are integrated into a morphological box. Morphological boxes are a common tool of displaying knowledge from systematic literature reviews (Nickerson et al. 2013). The dimensions of the morphological box (left side of Figure 13) reflect the most common properties of the different nudging studies. It is based upon the following dimensions: setting, choice architecture tool, category, application context, clusters of outcomes, data collection, significance, and magnitude (see Figure 13). Arrows indicate linkages among the dimensions.

- *Setting* describes whether a nudge is implemented in a conventional setting (e.g. Newell and Siikamäki 2013) or in a digital environment setting (e.g. Almuhimedi et al. 2015). This distinction is mainly derived from the recent proposition of “digital nudging” (Schneider et al. 2018; Weinmann et al. 2016), but we further differentiate between “digital nudge” and “digital setting” in the discussion (see also Chapter 4.1.6).
- *Choice architecture tool* describes whether the nudge is based on “structuring the choice task” or “describing the choice option” (Johnson et al. 2012). Tools for structuring the choice task "address the idea of what to present to decision-makers” while the latter “address the idea of how to present it” (Johnson et al. 2012, p. 488). Nudges can be traced back to one of these characteristics. This distinction is similar to the one of Münscher et al. (2016) which derive the categories of decision information, decision structure and decision assistance.
- The tools of choice architecture can be broken down into several *categories* (Sunstein 2014). For the category, we relied on existing frameworks for classifying nudges (e.g. Johnson et al. 2012; Münscher et al. 2016; Sunstein 2014). In particular, we have chosen to adapt the framework of Sunstein (2014), which is based on 10 different categories (Sunstein 2014). In most cases, each category could be matched with one of the two choice architecture tools.
- Moreover, the *application context* (hereafter just “context”) of the nudge is taken into account. The original work (Thaler and Sunstein 2008) already included health and wealth (hereafter “Finances”). Moreover, the related work (see Table 9) additionally provides the contexts of energy and environment. Based on the literature review, we also added policy making and the context of privacy.
- The *cluster of outcomes* reflect the contexts by including the most common dependent variables. As the outcomes are very heterogeneous, they were clustered, and the list of characteristics is not exhaustive. For example, energy consumption contains “electricity usage in kwh/day” (Allcott 2011), “kilowatt hours per week” (Guerassimoff and Thomas 2015) and “electricity consumption” (Sudarshan 2017).

- *Data collection* is self-explanatory. Most studies rely on different types of experiments, such as lab experiments, field experiments, or online experiments. In addition, surveys or survey experiments are also found occasionally. Sometimes the exact experiment type is not reported which is why we added the characteristic “Experiment (other)”.
- Finally, the *significance* and the *magnitude* are included. Significance is split up into statistically significant and statistically insignificant effects while both of them can be low, medium, or high in magnitude. The magnitude is defined as the relative effect size (see also Chapter 4.1.3).

Dimension	Characteristic									
Setting	Conventional					Digital				
Choice architecture tool	Structuring the choice task					Describe choice options				
Category	Default	Simplification	Social reference	Change effort	Disclosure	Warnings/ graphics	Precommitment	Reminders	Implement. intentions	Feedback
Application context	Health	Environment	Finances	Energy	Policy Making	Privacy				
Clusters of outcomes	Energy consumption	Healthy products chosen or purchase	Sales of environmentally friendly products	Amount donated	…					
Data collection	Online experiment	Lab experiment	Field experiment	Experiment (other)	Survey (experiment)					
Significance	Insignificant effect					Significant effect				
Magnitude	Low (<10%)	Medium (10%-30%)	High (>30%)							

Figure 13. Morphological box of experimental nudging studies

The morphological box provides a holistic overview of nudging. It can also be used to classify any nudges studies, to compare different studies, or to derive a research agenda.

Counting morphological box

To evaluate the morphological box, we coded the papers of the literature review. We marked relevant data points, transferred them to a spreadsheet, and counted them. This enables us to estimate which dimensions and characteristics have been researched to which extent. Some dimensions are evaluated at the level of a paper (100 papers in total), while others are better suited for evaluation on effect size level (319 effect sizes in total). There are more effect sizes than papers, because each paper can contain several nudging treatments or dependent variables (see Chapter 4.1.5 for more details). The difference of the counted characteristics to the 100 papers or 319 effect sizes in Figure 14 is usually unclear or multiple classifications. The result of the counting is displayed below.

Dimension	Characteristic									
Setting (100)	Conventional (68)					Digital (32)				
Choice architecture tool (306)	Structuring the choice task (119)					Describe choice options (187)				
Category (292)	Default (62)	Simpli-fication (12)	Social ref. (49)	Change effort (41)	Disclosure (18)	Warnings/ graphics (55)	Precommit-ment (6)	Reminders (34)	Implement. Intent. (8)	Feedback (7)
Application context (98)	Health (38)	Environment (19)	Finances (12)	Energy (10)	Policy Making (10)	Privacy (7)				
Clusters of outcomes (319)	Energy consumption (18)	Healthy products chosen or purchase (60)	Sales of environmentally friendly products (43)	Amount donated (20)	Other (178)					
Data collection (293)	Online experiment (46)	Lab experiment (47)	Field experiment (152)	Experiment (other) (6)	Survey (experiment) (42)					
Significance (310)	Insignificant effect (115)					Significant effect (195)				
Magnitude (273)	Low (<10%) (78)	Medium (10%-30%) (81)	High (>30%) (114)							

Figure 14. Morphological box of experimental nudging studies including counting

The figure shows a very diverse picture of nudging. 32 studies (32%) occur in digital settings while the majority takes place in conventional settings. When considering the tools of choice architecture, the studies are more biased towards describing the choice options (187 effects) compared with structuring the choice task (119 effects). Moreover, the category allows for an overview which nudges are used (effect size level). Defaults are most common (62 effect sizes). Next, there is an almost equal amount of social references (49), change effort (41), warnings/graphics (55), and reminders (34). Less common are simplifications, disclosures, precommitment strategies, eliciting implementation intentions, or feedback (only 51 effect sizes in total). One example of a simplification is provided by Malone and Lusk (2017) which reduced the number of alternatives and introduced special offers compared with a baseline selection of products.

Concerning the context, most studies are conducted in a health context (38), followed by environment (19). Less researched are finances (12), energy (10), policy making (10), and privacy (7). Interestingly, all studies that were conducted in a privacy context, were also conducted in a digital setting. In addition, most studies used some kind of experiment (82 studies), whereas surveys or survey experiments are less common (13 studies). Finally, about one third of the effects are statistically insignificant (115 effects) while the effect sizes almost split up evenly across low (78), medium (81), and high (114) magnitude.

Additionally, we tabulate the category and the context of the nudge (see Table 12). Thereby, we note that a high number of effects sizes in a health context were produced by the nudge of changing the effort, mostly by rearranging the cafeteria line (e.g. Wansink and Hanks 2013). Moreover, many studies in an environmental context used social references (e.g. Chang et al. 2016; Demarque et al. 2015) while the energy context relied mostly on disclosures (e.g. Newell and Siikamäki 2013). All precommitment nudges were used in a health context (e.g. Cohen et al. 2015).

Table 12. Category-context matrix of number of effect sizes								
Category	**Health**	**Environ-ment**	**Energy**	**Privacy**	**Finances**	**Policy making**	**n/a**	**Total effect sizes**
Default	9	18	4	3	15	3	10	**62**
Simplification	0	0	3	1	4	0	4	**12**
Social reference	3	26	4	2	8	6	0	**49**
Change effort	35	1	0	0	0	4	1	**41**
Disclosures	0	0	16	2	0	0	0	**18**
Warnings	17	11	0	13	0	4	10	**55**
Precommitment	6	0	0	0	0	0	0	**6**
Reminders	11	1	0	0	10	12	0	**34**
Implementation intentions	0	4	3	0	0	1	0	**8**
Feedback	3	0	2	0	0	2	0	**7**
n/a	13	10	0	1	3	0	0	**27**
Total effect sizes	**97**	**71**	**32**	**22**	**40**	**32**	**25**	**319**

Further, we performed in-depth analyses on the publication year, the context, the category, and the origin of the sample.

Publication year, category, context, and country

Looking at the years of the publication reveals that the number of studies is growing steadily each year. While the first studies appeared shortly after the original book on nudging (Thaler and Sunstein 2008), the year 2017 marked an all-time high of studies using nudges. Throughout the last years, there seems to be a positive trend in terms of absolute numbers of nudging publications.

We broke down the nudging categories for each year (see left side of Figure 15) and note that defaults and social references have always been popular. The use of warnings/graphics has not started until 2012, but most studies from 2017 have used this category. We repeat the same exercise for the context and the publication year (see right side of Figure 15). Most studies were conducted in the health context followed by environment. Not much variation is noted for the contexts of health and environment which are reasonably stable across all years. Overall, the three contexts of energy, environment and health cover 2/3 of all studies.

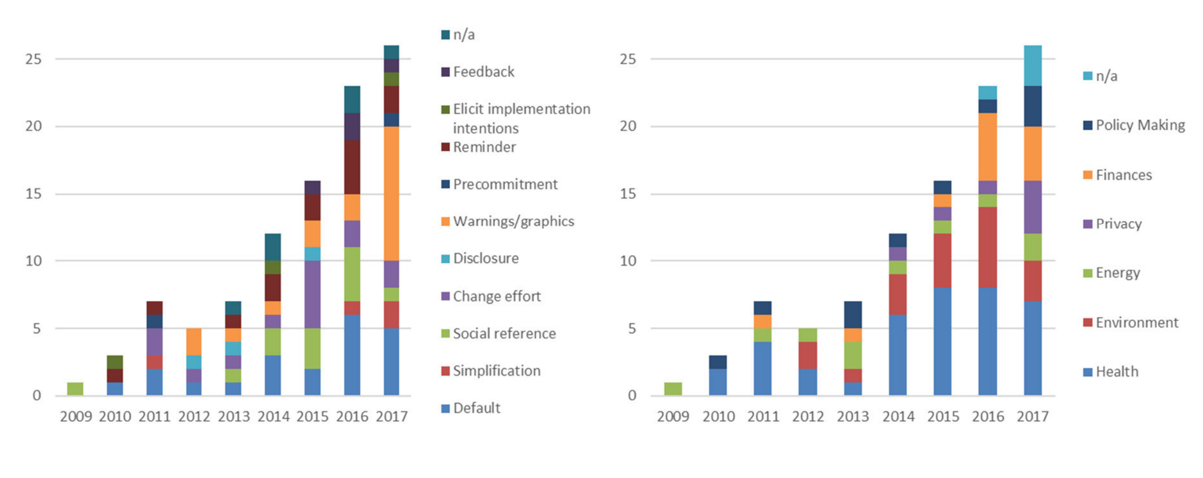

Figure 15. Distribution of papers according to category (left) and context (right) per year

If we consider the location of the studies, 40% of the studies are conducted in the United States (40). If Europe is taken together, 41 studies were conducted here, with UK at the top (7 studies). Only few studies have been conducted in Africa (e.g. Duflo et al. 2011) or Asia (e.g. Agarwal et al. 2017; Sudarshan 2017). The Latin American continent remains largely uncovered. It is important to note that the studies from Asia and Africa have been published in the last two years (Agarwal et al. 2017; Sudarshan 2017) so more studies might be in the pipeline. Next, we turn to the quantitative analysis of the effect sizes.

4.1.5 Results Quantitative Analysis

For the quantitative analysis, all coded variables are analyzed according to context, category, relative effect sizes, and others. Finally, we derive implications for digital nudging.

Data quality

A main contribution is the estimation of effects and effect sizes. The results of the 100 papers comprise 319 effect sizes. The number of effect sizes is greater than the actual number of papers for several reasons. Firstly, one paper usually comprises several experiments. On average, each paper consists of 1.36 experiments with a maximum of 8 experiments in one paper (Goswami and Urminsky 2016). Secondly, many papers report several dependent variables for one nudge, especially in a health context (Cohen et al. 2015; Wansink and Hanks 2013). Thirdly, one experiment consisted of several nudges that were tested against each other on one or more dependent variable (e.g. Friis et al. 2017). For the effect sizes, we always used a positive value even though some studies aimed to reduce the outcome compared with the control group (e.g. less energy used). Yet, not all papers report all coded variables. Therefore, Table 13 presents the number of data points for each variable (max. 319 possible).

Table 13. Overview of data points of quantitative analysis				
Tool of choice architecture	**Nudge category**	**Effect (Yes/No)**	**Relative effect size**	**p-value**
n = 306	n = 292	n = 310	n = 273	n = 230

Effects and effect sizes

Of the 310 effects (see Table 13), 195 effects (63%) have a statistically significant effect, which is mostly reported as a p-value of 0.05 or lower, while 115 effects (37%) are statistically insignificant, which is mostly reported with a p-value of more than 0.05. Occasionally, statistically insignificant effects are reported to be insignificant in the discussion section of the primary publications, and not in the respective results section. Some studies claim that a p-value below 0.10 is still statistically significant, yet we labelled them as insignificant as we used a hurdle rate of 0.05. Only for 9 effects neither the p-value nor the statistical significance is reported. Hence, about 63% of the nudges have a statistically significant effect and 37% have an insignificant effect.

Overall, nudges have a median relative effect size of 21%. This effect sizes ranges from 0% (Damgaard and Gravert 2016) to 4400% (Steffel et al. 2016) and it includes both statistically significant and insignificant effects. Steffel et al. (2016) report on a default nudge that increases the choice of whipped cream on a hot chocolate from 2% to 90% (relative change of 4400%). The average relative effect size is 77%, but a few extremely high values artificially raise the effect size. If we exclude values of more than 150%, then the average effect size is still at 30%. The lowest statistically significant effect size is 1.8% (Goswami and Urminsky 2016) which might be due to the high sample size of 3,486 participants. Statistically significant effects have a median (average) relative effect size of 37% (110%), while insignificant effects have a median (average) effect size of 7% (17%). Furthermore, we estimate the effect sizes depending on the context (Table 14 and Figure 16) and the nudge category (Table 15 and Figure 17).

Effect sizes by application context

Splitting up the studies by context shows the effect sizes across the different contexts.

Table 14. Average and median effect sizes per context						
Context	**Energy**	**Environment**	**Finances**	**Health**	**Policy making**	**Privacy**
# of studies (# of effects)	10 (21)	19 (69)	12 (37)	38 (86)	10 (26)	7 (13)
Median effect size	13%	39%	28%	22%	6%	44%
Average effect size	24%	37%	35%	28%	8%	33%

The information is also visualized in the following boxplot (see Figure 16).

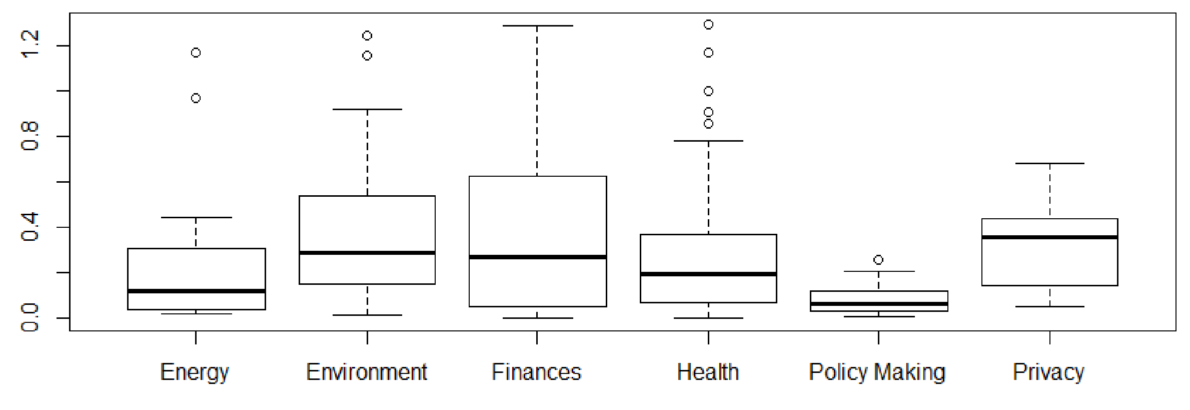

Figure 16. Boxplot of relative effect sizes per context

Table 14 and Figure 16 highlight that the effect sizes vary by context. While the effect sizes for environment, finances, and health are similar, the median for energy (privacy) seems to lower (higher). The quartiles for finances are the largest despite a low number of studies.

To validate this result statistically, we conducted an analysis of variance (ANOVA) with the effect size as the dependent variable and the context as the independent variable. This yields a statistically significant difference between the contexts. Values higher than 150% were excluded from the average effect size calculation, the boxplots and the ANOVA not to distort the results.

Effect sizes by nudging category

Next, we turn to the effect sizes per nudge category (see Table 15 and Figure 17).

Table 15. Average and median effect sizes per category of nudge

Nudge	**#1**	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
# of studies (# of effects)	21 (62)	4 (12)	12 (49)	14 (41)	3 (18)	18 (55)	2 (6)	13 (34)	3 (8)	4 (7)
Median effect size	51%	25%	21%	25%	11%	20%	7%	8%	39%	20%
Average effect size	50%	24%	27%	30%	20%	30%	7%	22%	20%	23%

#1 Default; #2 Simplification; #3 Social reference; #4 Change effort; #5 Disclosure; #6 Warnings/graphics; #7 Precommitment; #8 Reminders; #9 Elicit implementation intentions; #10 Feedback

It becomes apparent that each nudging category has a different effect size. Thereby, especially defaults have larger median and average effect sizes than other categories. The median and average effect sizes of the other categories are closer together. Yet, it has to be noted that some categories (e.g.

precommitment, elicit implementation intentions, and feedback) have low samples of studies so that those results are less reliable. The data is additionally visualized in Figure 17.

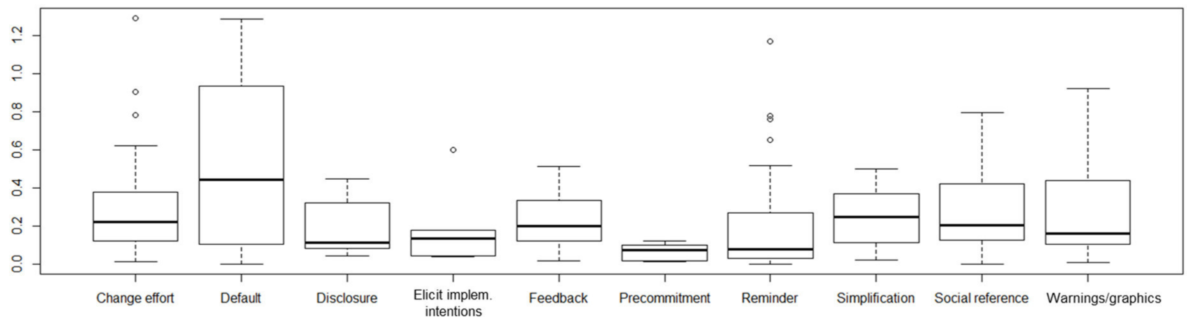

Figure 17. Boxplot of relative effect sizes per category of nudge (alphabetical order)

To estimate the differences, we again run an additional ANOVA with the category as the independent variable and the effect size as the dependent variable. This yields a statistically significant effect which implies that some of the categories have different means. This is particularly true for the default category. Again, values higher than 150% were excluded from the average effect size calculation, the boxplots and the ANOVA not to distort the results.

Digital nudging

Finally, we report separately on studies in a digital setting, or using digital nudging. We defined a digital setting when an information technology (IT) was involved in the nudge (e.g. a reminder via e-mail). In turn, digital nudging, as defined by Weinmann et al. (2016), only involves user-interface design elements. To stay with the previous example, we do not consider the reminder e-mail a user-interface design element. Therefore, digital nudges are a sub-dimension of studies in a digital setting.

32 studies have used nudges in a digital setting (e.g. Rodríguez-Priego et al. 2016; Székely et al. 2016). Thereof, only 19 studies have actually manipulated the user-interface (Esposito et al. 2017; Huang et al. 2017; Rodríguez-Priego et al. 2016). Examples are different designs of a search engine (Rodríguez-Priego et al. 2016), using defaults to increase privacy protection (Baek et al. 2014), or using labels to increase sustainable consumption (Demarque et al. 2015). Moreover, we found a variety of research-in-progress papers on digital nudging (Djurica and Figl 2017; Hummel et al. 2017a; Pahuja and Tan 2017), although these were not included in the systematic literature review. Surprisingly, most studies only use the user screen (e.g. for e-mails), and only few studies use different information technology, such as eye-tracking (Hummel, Toreini, and Maedche 2018) or neurophysiological measurements (Jung and Dorner 2018) for nudging.

Finally, we conducted an ANOVA to estimate whether conventional nudges differ from nudges in a digital setting. Therefore, we used the binary information digital setting (yes/no) as an independent variable and the effect size as a dependent variable. The result is statistically insignificant. Hence, the effect sizes of nudges in digital settings are not different to the effect sizes of nudges in conventional settings. Values higher than 150% were excluded from the ANOVA not to distort the results.

Subsequently, we discuss the results and derive several research streams for the IS community.

4.1.6 Discussion and Avenues for Future Research in Digital Nudging

Discussion of results

Nudging is seen as a salvaging concept across many disciplines. As it is also applied in policy making, it affects all citizens which underlines the importance of a scientific evaluation. We started from the notion that nudging might be less effective than proclaimed. This notion is partly supported as 63% of the nudging treatments have a statistically significant effect. In the following, the results are discussed along the dimensions of the morphological box: setting, choice architecture tool, category, application context and clusters of outcomes, significance and magnitude.

Setting: The setting focuses predominantly on conventional nudging although digital settings are studied to an increasing extent. Particularly in the last two years, 2016 and 2017, there has been the same amount of studies in a digital and a conventional setting. Although a digital setting has been used quite frequently, many studies did not adhere to the definition of "digital nudging" by Weinmann et al. (2016) (e.g. Esposito et al. 2017; Huang et al. 2017). This raises issues of competing definitions as other researchers start to come up with their own ones (e.g. Meske and Potthoff 2017). Moreover, an increasing number of papers propose study designs that are not in the interest of the decision-maker but the choice architect (Abdukadirov 2016; Lehrer and Jung 2017). This trend is likely to increase as providers of digital channels can easily implement digital nudges to promote sales in digital channels. Finally, in terms of effect sizes we find no difference between the digital and the conventional setting.

Choice architecture tool: Most studies "describe choice options" which can be traced back to a broad range of interventions such as social reference (e.g. Allcott 2009), simplification (e.g. Cyan et al. 2017), or reminders (e.g. Sonntag and Zizzo 2015). The difference would be even more pronounced if fewer studies had used defaults which counts as "structuring the choice task" (Johnson et al. 2012). As merely describing choice options is less invasive in terms of paternalism (Johnson et al. 2012; Thaler and Sunstein 2003), this finding supports the idea that most choice architects in the primary publications balanced the need for pushing individuals in one direction with the criticism of paternalism. This has been particularly pronounced in the context of privacy where only few studies used a form of "structuring the choice task" (e.g. Baek et al. 2014; Dogruel et al. 2017) and most relied on "describing choice options" (e.g. Esposito et al. 2017; Rodríguez-Priego et al. 2016).

Category: Along with the choice architecture tool, the category of nudge varies in the primary publications. While defaults and social references were used frequently (e.g. Demarque et al. 2015; Goswami and Urminsky 2016; Theotokis and Manganari 2015), other measures are less common. We assume that defaults are easy to implement and allow for a more precise causality of treatment and outcome than multi-step nudges such as eliciting implementation intentions or precommitment strategies (e.g. Nickerson and Rogers 2010). In turn, social references are more complex to implement but allow for a richer content, and they are thus more interesting from a psychological point of view (see publications in psychological journals such as Aldrovandi et al. 2015; Demarque et al. 2015; Hilton et al. 2014). Moreover, we note an overlap of the nudge category with the application context (see Table 12). For example, most nudges in the privacy context are warnings (e.g. Rodríguez-Priego et al. 2016; Schneider et al. 2018), the majority in a health context used changing effort (e.g. Wansink and Hanks 2013; Cohen et al. 2015), whereas the majority in finances used reminders or defaults (e.g. Goswami and Urminsky 2016). We conclude that there exist category-context associations in nudging whereas it remains unclear why this is the case.

Application context and clusters of outcomes: We note a concentration on the health context although a variety of other contexts are employed, too. What is surprising, is the low percentage of studies with personal finances (e.g. Cyan et al. 2017; Zarghamee et al. 2017) as the claim of the original book was to "improve decisions about health, *wealth*, and happiness" (Thaler and Sunstein 2008). However, the concentration on the health context was to be expected as most of the literature reviews were conducted in this context, too (e.g. Bucher et al. 2016; Wilson et al. 2016). The reason for this overrepresentation might be that the health context was already very prominent in the original work of Thaler and Sunstein (2008), and that it offers better access to data as well as already established randomized controlled trials (RCTs). The clusters of outcomes are interconnected with the application context and we note that similar constructs (e.g. energy consumption) are measured quite differently ranging from "electricity usage in kwh/day" (Allcott 2011), "kilowatt hours per week" (Guerassimoff and Thomas 2015), or "kilowatt hours purchased per billing cycle" (Costa and Kahn 2011). This underlines the importance of using a meta-level measurement such as the relative change in the dependent variable.

Significance and magnitude: The most important contribution of this study is on the effect sizes of nudges. The quantitative analysis shows that the effect sizes are very diverse. Most importantly, it is astonishing for us to see that about 1/3 of the effects are statistically insignificant. Most likely, this number is even too low when considering that many studies with insignificant results do not get published ("publication bias"). Therefore, also the median (average) effect size of 21% (77%) is rather overestimated. Nevertheless, it is valuable to find out that default nudges seem to be more effective than any other nudge category (see Table 15). This can be explained by the status quo bias (Samuelson and Zeckhauser 1988) and decision inertia (Alós-Ferrer et al. 2016; Jung and Dorner 2018) that are particularly vulnerable to defaults. We are not aware of other studies that ranked nudges by their effectiveness. Hence, we cannot compare it with previous studies or integrate it in the current state of research. Moreover, although not being part of the morphological box, some studies foreshadow moderating effects on the effectiveness of nudging, such as political preferences (e.g. Fellner et al. 2013) or personality (Jung and Mellers 2016; Stutzer et al. 2011). For example, Stutzer et al. (2011) measure the Big Five personality traits and find that conscientiousness might explain some of the differences in blood donation behavior when using defaults. This is an important finding as the effectiveness of nudges seems to not only depend on the nudge itself, but also on how it is perceived by an individual. However, many studies did not publish standard deviations and p-values along with the effect sizes. This limits the possibilities to run additional calculations using other measures such as Cohen's d (Cohen 1988) or to include quality measures like the Quality Assessment Tool for Quantitative Studies (Lycett et al. 2017). In sum, nudges seem to work but the effect sizes are influenced by the application context and especially by the nudge category.

As digital nudging will be more important in the future given an increased decision-making in digital environments, we synthesize the results in six avenues for future research in digital nudging.

Avenues for future research in digital nudging

The avenues for future research, derived from the systematic literature review and quantitative analysis, are illustrated along the digital nudging cycle (adapted from Schneider et al. 2018) in Figure 18 below.

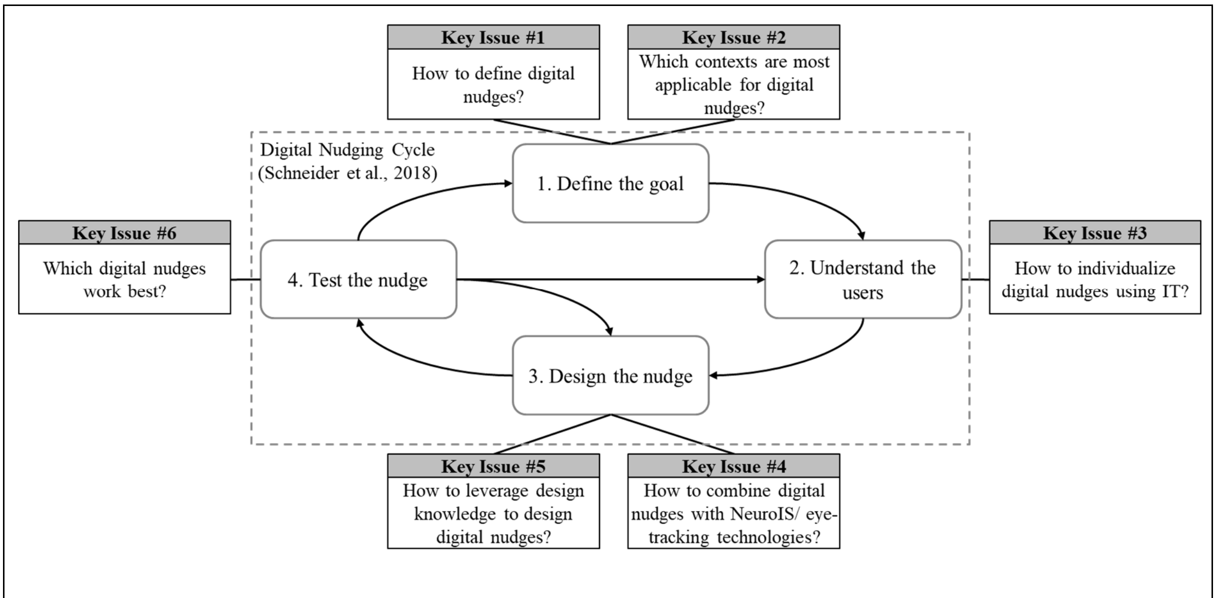

Figure 18. Avenues for future research along the digital nudging cycle

When *defining the goal*, it is important to state the definition of digital nudging. Is it using any kind of digital technology (as we defined digital setting)? Or rather the use of user-interface design elements to guide people's behavior in digital choice environments (Weinmann et al. 2016)? Hereby, we also refer to the discussion on the *setting* above. In addition, the most applicable and promising contexts need to be determined by future research. To *understand the users*, it is crucial to understand the interplay between digital nudges and the individual characteristics (see discussion above on *significance and magnitude*). Moreover, it would be important for the IS community to research which IT is most useful for individualizing digital nudges. When *designing the nudge*, we see two research opportunities based on the findings of the systematic literature review. On the one hand, a methodological approach is helpful when designing digital nudges. Although several researchers have suggested such processes (Meske and Potthoff 2017; Schneider et al. 2018), a design science research (DSR) approach (Arnott 2006; Kuechler and Vaishnavi 2008) would be beneficial to derive theory-grounded design principles. On the other hand, digital nudging, as opposed to conventional nudging, could benefit from an increased usage of alternative information technology, such as eye-tracking technology, virtual reality, or neurophysiological measurements. Given that such technology plays an increasing role in decision-making (Innocenti 2017), it is imperative to study the effects of digital nudges in such cases. Finally, *testing the nudge* is the conclusion of all previous research questions to find out which digital nudges work best. While we know that defaults are most effective in a conventional setting, it is unclear whether this is also true for digital nudges. To answer this research question, we are lacking sufficient evidence of testing different digital nudging treatments against each other. The avenues for future research are synthesized in Table 16 below.

Table 16. Key challenges and research streams in digital nudging for the IS community

#	Key issue	What we know – current evidence	Key challenges
1	How to define digital nudges?	1. One definition has been proposed 2. More approaches exist that leverage IT but do not use UI design elements 3. Many nudges and digital nudges are not in the interest of the decision maker but in the interests of the choice architects	1. How to integrate digital nudges that do not manipulate the UI into a coherent definition? 2. How to account for the interests of the decision maker? Who defines their interests in a digital setting?
2	Which contexts are most applicable for digital nudges?	1. Effect sizes for conventional nudges vary for the different contexts 2. Weinmann et al. (2016) suggested several contexts and use cases for digital nudges	1. Only few empirical studies exist, which have not covered all contexts for digital nudges 2. Some contexts of offline nudges less relevant, but new ones arise (e.g. business process management)
3	How to individualize digital nudges using IT?	1. Conventional nudges are rarely individualized 2. IT offers the possibility to individualize by adapting the user interface to the characteristics or the behavior of the users	1. Which digital nudges work best for which individual characteristics? 2. Which IT is best suited to generate and implement individualized digital nudges?

4	How to combine digital nudges with NeuroIS/ eye-tracking?	1. Very often, nudges are ineffective or even lead to backfire effects 2. NeuroIS and eye-tracking offer possibilities to react to ineffective digital nudges in real-time	1. How to combine digital nudging with NeuroIS or eye-tracking? 2. Does the integration of technologies lead to better or worse effects of digital nudging?
5	How to include DSR to design digital nudges?	1. Several approaches to design digital nudges (e.g. Meske and Potthoff 2017) 2. DSR emerged as a possible theoretical basis for designing theory-grounded digital nudges	1. Existing approaches have not been validated empirically 2. How to integrate DSR into the process of designing digital nudges?
6	Which digital nudges work best?	1. In a conventional setting, default nudges work best 2. The effect sizes of digital nudges are not significantly different from nudges in conventional settings based on our QA	1. Small empirical base of digital nudging studies to analyze the effectiveness of digital nudging 2. Nudges in digital settings are very heterogeneous, from e-mail reminders to the design of a search engine

4.1.7 Conclusion

Nudging and digital nudging receive increased attention from academia and practice. After reviewing existing literature reviews in the sphere of nudging, we conducted a quantitative literature review. By analyzing 100 studies, we develop a morphological box and analyze the different properties of (digital) nudging. Most importantly, we derive insights for the effectiveness of nudges.

This study makes several contributions to the theory and practice of behavioral and experimental economics. Besides creating a theoretical framework for empirical nudging studies by means of a morphological box, we assess the overall effectiveness of nudging and claim that it might be less effective than proclaimed. We show that this can, in part, be related to the category and the context of the nudge, and we provide avenues for future research in digital nudging.

By making the data of the 100 coded papers available to all researchers, the authors aim to contribute to the discussion on the effectiveness of (digital) nudging and to refine the concept for future research. These contributions are particularly helpful as tools of behavioral economics are gaining increasing popularity in various research disciplines, and as a comprehensive and holistic overview of the nudging concept is likely to accelerate these research activities. Furthermore, we also offer implications for practitioners. Especially government officials, that are responsible for nudging activities in policy making, can use our results to improve policy making in various fields. These suggestions are in line with the propositions of other researchers (Datta and Mullainathan 2014; Ly et al. 2013).

The study has several limitations. First, we did not use several researchers for extracting the information from the selected papers due to the large amount of studies. Yet, as ambiguous sections were discussed with a knowledgeable researcher, the benefit of using an additional coder is considered to be low. In addition, extracting quantitative effect sizes from primary publications leaves less room for interpretation than coding qualitative data, such as interviews. Moreover, we might be victim to a possible publication bias as many studies with insignificant results are often not published. This implies that the findings are rather on the upper, edge and including several insignificant results would rather lower the average effect sizes. Moreover, we only included studies that mentioned the concept of nudging or referenced the work of Thaler and Sunstein (2008). Thereby, we are able to guarantee the comparability of the selected studies, but we might have excluded studies with a similar focus. Yet, as our work is comprehensive with 100 studies, we believe that the few nudge-like studies would not have made a large difference. To support this claim, we additionally coded and analyzed a randomly selected sample of 20 nudge-like studies. We compared them with the results of this study and could not find major differences (full results not disclosed).

Our study can only be a first step and further research is needed on this matter. The key challenges and research streams in digital nudging for the IS community provide sufficient content for future research. In addition, future research should include other nudge-like studies and compare the results with the conclusions drawn from this work. Finally, it would be beneficial to include a quality rating of the selected studies, similar to Lycett et al. (2017), to weigh them accordingly, and to prevent that lower quality studies distort the results of high-quality ones.

An overview of all studies included in the systematic literature review and quantitative analysis can be found in Appendix D. The findings on diverging effect sizes and potential moderating effects on the effectiveness of nudging were tested in an experimental setting in the following study.

4.2 Study 4: Individualized Digital Nudges for Sustainable Choices in Digital Retail Channels[4]

4.2.1 INTRODUCTION

Sustainability is one of the key challenges of our time (United Nations 2018). Many consumers want to contribute to a more sustainable world, for instance by purchasing and consuming sustainable products (Teng and Wang 2015; Yadav and Pathak 2016). Although many consumers would like to buy more sustainable products, only 20% do so regularly (Kristensson et al. 2017). This is also known as an "attitude-behavior gap" since the attitude towards a certain behavior is often a poor predictor of the actual marketplace behavior (Ajzen 2001; Vermeir and Verbeke 2006). In addition to consumers, vendors would also benefit from an increased sale of sustainable products as these products usually have higher profit margins. Hence, the actual purchasing decisions are not optimal for either side, consumers and suppliers. Moreover, the environment would also benefit from increased digital sales of sustainable products, making it a win-win-win situation.

One possibility to increase the consumption of sustainable products is using tools of choice architecture, so-called "nudges" (Thaler and Sunstein 2008). Nudges have been used in the past to promote sustainable behavior (e.g. Campbell-Arvai et al. 2014; Theotokis and Manganari 2015). Yet, nudges have been failing regularly in recent studies (e.g. Momsen and Stoerk 2014; Sonntag and Zizzo 2015), and Sunstein recently published a paper on "nudges that fail" (Sunstein 2017). A possible explanation for the observed failures might be that these nudges have been selected and deployed randomly and were not individualized according to the consumer characteristics. Individualization means that nudges are adapted to meet certain needs and preferences of consumers. Individualization of nudges was suggested by various studies in different settings (e.g. Goldstein et al. 2008; Halpern 2016; Johnson et al. 2012), but has not been verified empirically with personality traits or other individual characteristics. Individualization of nudges is difficult in conventional settings but more promising when digital environments are concerned ("digital nudging"), which also become increasingly important as sales channels for sustainable products.

Digital nudging describes "the use of user-interface design elements to guide people's behavior in digital choice environments" (Weinmann et al. 2016). Digital nudges have been used successfully in online contexts to increase the consumption of sustainable products (e.g. Demarque et al. 2015) or to increase CO_2 offset payments (Székely et al. 2016). Yet, also in digital settings, the individual consumer characteristics have not been considered so far, and little is known about the interplay between different digital nudges and individual consumer characteristics. This is despite an increasing growth and availability of consumer and usage data that can be used for an individualization, e.g. by determining

[4] This section is based on Hummel, Vogel and Maedche (2018)

personality traits based on social media data (Markovikj et al. 2013; Youyou et al. 2015). One reason for this lacking individualization might be that designers of digital channels lack the required knowledge to match individual consumer characteristics with the design of their digital choice environments.

In this context, personality traits are a promising individual characteristic for the individualization as they have proven to be a differentiating factor in earlier studies using online contexts (e.g. Bansal et al. 2010). The Big Five Inventory (McCrae and John 1992) is the most prominent inventory of personality traits. Personality traits have an influence in various fields of IS research, e.g. in various forms of decision support (e.g. Bansal et al. 2010), or to advance the TAM (e.g. Svendsen et al. 2013). In the context of nudging, only few studies have included personality traits (Jung and Mellers 2016; Stutzer et al. 2011), all of which have some drawbacks. For example, Jung and Mellers (2016) measured only attitudes towards nudges and not treatment effects. Therefore, we hypothesize that it is promising to research the interaction effects of digital nudges and personality traits to increase sustainable product choices. Overall, the following research question shall be answered:

Research Question*: How do different types of digital nudges (defaults, social norms and warnings) influence the choice of sustainable products in digital channels under consideration of personality traits?*

In order to answer the research question, we conducted an online survey experiment with 452 participants. The participants were presented a non-branded online grocery store similar to existing shops of Rewe (Germany), Sainsbury's (UK), or Kroger (USA). The participants were asked to select several products while being digitally nudged towards the sustainable alternative.

This study contributes to existing IS research in several ways. Firstly, our study contributes empirically to the emerging field of digital nudging. It offers one of the first digital nudging studies that tests different digital nudges against each other. Thereby, it is a valuable finding that digital nudges can do both harm and good. Secondly, we show that these effects are reinforced or diminished dependent on personality traits. In particular, defaults interact positively with openness, while warnings interact negatively with conscientiousness. As far as we know, this moderating effect has been proposed theoretically (e.g. Goldstein et al. 2008; Halpern 2016; Johnson et al. 2012), but not verified empirically.

Practitioners of different areas can use our results. Designers of digital channels can implement (personality) adaptive digital nudges which take into account the individual characteristics of the decision-makers. Thereby, they can increase the effectiveness of digital nudges and reduce the chance of unintended outcomes. In addition, policy makers can implement the findings in tailoring environmentally friendly policies, for example by using defaults rather than social norms to promote sustainable consumption. This helps governments to reach environmental goals, or the international community to achieve the Sustainable Development Goals (SDGs) of the United Nations (United Nations 2018).

The rest of this study is organized as follows: Chapter 4.2.2 describes the theoretical concepts and related work of sustainable consumption, (digital) nudging, and personality traits. Moreover, it derives the hypotheses for the direct effects of the digital nudges, the interaction effects of the personality traits, and it depicts the research model. In Chapter 4.2.3, the experimental design and the data collection methodology is presented. Afterwards, Chapter 4.2.4 presents the descriptive results and the outcomes of the regression models. Chapter 4.2.5 discusses the findings, while Chapter 4.2.6 concludes the study by describing the limitations as well as giving an outlook on future research.

4.2.2 Theoretical Background and Hypotheses Development

Attitude-behavior gap in sustainable consumption

Online sales of groceries is an emerging topic in IS and marketing research (Melis et al. 2015). Within this topic, especially sustainable consumption has been researched extensively (e.g. Joshi and Rahman 2015; Prothero et al. 2011). For sustainable consumption, it is particularly striking that many consumers report that they want to buy sustainable products, but that they fail to turn this behavior into action, also labelled “attitude-behavior gap” (Ajzen 2001; Joshi and Rahman 2015; Vermeir and Verbeke 2006). This has led to the conclusion that theory of planned behavior (Ajzen 1991) is not suitable to explain sustainable consumption (Joshi and Rahman 2015), but that both individual and situational factors are also relevant factors in sustainable consumption decisions (Joshi and Rahman 2015; Prothero et al. 2011). Individual factors are emotions and habits, but also values and personality, while situational factors are represented among others by (online) store related attributes (Joshi and Rahman 2015). In online contexts, such attributes are determined by an information system. Hence, IS researchers have recognized that the design of information systems can contribute to environmental sustainability (Hamari et al. 2016; Melville 2010). Thereby, especially tools of choice architecture, so-called nudges, are suitable to increase sustainable consumption and to reduce a potential attitude-behavior gap. Table 17 provides an overview of the related work on the use of nudges in a sustainability context or the use of nudges and personality traits in other contexts.

Table 17. Related work on nudging and personality traits in a sustainability context					
Study	**Context**	**Dependent variable**	**Nudges**	**Data collection**	**Personality traits**
Stutzer et al. (2011)	Donations	Blood donations	Defaults	Field experiment	Big Five Inventory
Löfgren et al. (2012)	Sustainability	CO2 compensation (binary)	Defaults	Field experiment	n/a
Campbell-Arvai et al. (2014)	Sustainability	Participants choosing meat free option	Defaults, warnings	Field experiment	n/a
Demarque et al. (2015)	Sustainability	Sustainable products	Social norms	Lab experiments	n/a
Theotokis and Manganari (2015)	Sustainability	Towel reuse and activation e-statements	Defaults	Multiple sources	n/a
Egebark and Ekström (2016)	Sustainability	Pages printed	Reminder, defaults	Field experiment	n/a
Hedlin and Sunstein (2016)	Sustainability/ energy	Enrollment rate green energy	Defaults	Online experiment	n/a
Jung and Mellers (2016)	Multiple contexts	Attitude towards nudges	n/a	Online survey	Empathetic, desire for control, reactant, individualist, conservative
Székely et al. (2016)	Sustainability	Amount of CO2 donations (in €)	Defaults	Online experiment	n/a
Graham and Abrahamse (2017)	Sustainability	Meat consumption, attitudes towards eating meat	Informational nudge, framing	Online survey	n/a
Puaschunder (2017)	Sustainability	Recycled disposable weight	Warnings	Field experiment	n/a[5]
This study (2018)	Sustainability	Sustainable product choices	Defaults, social norms, warnings	Online survey experiment	Big Five Inventory

[5] The authors report on the trait of conscientiousness which does not refer to the identical personality trait of the Big Five Inventory but to the general awareness of a sustainable, environmental behavior

Table 17 shows that numerous studies have implemented nudges in a sustainability context but only few of them have investigated the relationship of nudging and individual characteristics, particularly personality traits. Only one study has used the Big Five Inventory (Stutzer et al. 2011), whereas another study assessed attitudes towards nudges and not their effectiveness (Jung and Mellers 2016). Yet, both studies have some drawbacks. For example, Stutzer et al. (2011) employ one treatment (defaults) and hypothesize that only conscientiousness might explain some of the differences in blood donation behavior. Moreover, most studies were conducted in conventional settings, and thus it remains unclear which nudges work best in digital environments. It is also open whether digital nudges can be individualized according to the individual traits of consumers, particularly personality traits. To conclude, there is a growing need to study the interaction of digital nudges and personality traits due to an increasing online purchasing behavior as well as an attitude-behavior gap in sustainable product choices.

Nudging and digital nudging

The concept of nudging is widely applied, and the original work of Thaler and Sunstein (2008) has been cited more than 10,000 times. Nudges make use of heuristics and cognitive biases in human decision-making, such as loss aversion or framing (Kahneman and Tversky 1979; Thaler and Sunstein 2008; Tversky and Kahneman 1981). Recently, the concept has been extended to digital environments (Weinmann et al. 2016), and also the head of the British Behavioral Interventions Team expects the digital sphere to be the next step in nudging (Halpern 2016). Digital nudges are increasingly important as more and more time, money, and decisions are spent or made online. Hence, IS researchers are producing experimental designs (e.g. Hummel et al. 2017; Székely et al. 2016), or conceptual papers (e.g. Gregor and Lee-Archer 2016) on digital nudging. Nudges have been used before in settings of environment and sustainability (e.g. Demarque et al. 2015; Hedlin and Sunstein 2016; Székely et al. 2016), or in a context of healthy eating (e.g. Cioffi et al. 2015). To classify nudges, one of the authors of the original book defined 10 different types of nudges (Sunstein 2014). Based on this categorization, we conducted a quantitative analysis (Hummel and Maedche 2018) and identified defaults, social norms and warnings to be most effective and most suitable in our context.

For *defaults*, we rely on a definition that describes a default as a "condition that is imposed when an individual fails to make a decision" (Johnson and Goldstein 2003). In other words, defaults refer to choice conditions in which one of the choice options is pre-selected. Defaults are multi-faceted nudges with regard to their underlying mechanisms. Many researchers argue that defaults make use of the status quo bias (Samuelson and Zeckhauser 1988) which is characterized by disproportionately sticking with the status quo even when the benefits of changing outweigh the status quo (Samuelson and Zeckhauser 1988). Either, individuals stay with the default because changing the pre-selected option is associated with transaction costs (e.g. Thaler and Benartzi 2004), or because the decision maker is indifferent to the choice options. Alternatively, a default can be regarded as an implicit recommendation by the choice architect for a difficult choice (McKenzie et al. 2006). Numerous studies have implemented defaults in a variety of contexts, e.g. to increase blood donations (Stutzer et al. 2011), or to nudge individuals to compensate their CO2 emissions (Löfgren et al. 2012; Székely et al. 2016). Defaults are considered one of the most powerful nudges (Goldstein et al. 2008). Hence, we hypothesize:

Hypothesis 1 (H1)*: Digital nudges of the type default positively influence sustainable product choices.*

Next*, social norms* are "rules and standards that are understood by members of a group, and that guide and/or constrain social behavior without the force of law" (Cialdini and Trost 1998, p. 152). Social norms can be differentiated between descriptive norms and injunctive norms (Cialdini 2003). Descriptive norms reveal what most people would do or have done while injunctive norms indicate which choice would be morally expected. Norms can be established by normative messages, for example as communicated by an authority. However, due to social comparisons, norms can also result from the observation of others. In this vein, the behavior of others acts as a social proof that an individual is showing the adequate behavior in the decision situation. Thus, an important information in the situation is what other do (or did), which acts as a descriptive norm. In other words, social norms work because people have the tendency to follow the majority, because they take the behavior of others as a social proof, and because they use the behavior of others to infer which is the best option (Cialdini 2003; Cialdini and Trost 1998). Social norms have been implemented by various studies (e.g. Aldrovandi et al. 2015; Demarque et al. 2015; Hermstrüwer and Dickert 2017). As social norms advertise the choice of sustainable products, we assume:

H2*: Digital nudges of the type social norms positively influence sustainable product choices.*

Warnings emphasize the negative consequences when consumers do not show the intended behavior, such as selecting the sustainable product, but show the alternative behavior instead. In the consumer literature, this can be regarded as a negative frame because providers do not display the benefits of showing the desired behavior, but emphasize the adverse consequences if one does not engage in this behavior (Ganzach and Karsahi 1995; Krüger et al. 2016). Thereby, warnings typically take advantage of the loss aversion of individuals (Kahneman and Tversky 1979) by emphasizing risks and potential disadvantages of a choice. Warnings can be for example "large fonts, bold letters, and bright colors" to trigger people's attention (Sunstein 2014, p. 5). Warnings have been used in the past in offline contexts (e.g. Cioffi et al. 2015; Thorndike et al. 2014). Typically, they were implemented as traffic-light labels (see Seward et al. 2016; Thorndike et al. 2012, 2014). Similarly, warnings in an online context put an extra burden on selecting unsustainable products. Hence, we hypothesize:

H3*: Digital nudges of the type warnings positively influence sustainable product choices.*

More importantly, the effect of digital nudges on sustainable product choices depend on individual characteristics, in particular on the personality traits, of the participant. This was shown by earlier studies which found that nudges interact with (political) attitude (Costa and Kahn 2011), that the attitude towards nudges is influenced by personality traits (Jung and Mellers 2016), and that nudges work the best if they are individualized according to the decision maker's personal characteristics (Johnson et al. 2012; Schneider et al. 2018). Moreover, we focus in particular on personality traits as a moderator as they have proven to be distinctive in earlier studies using similar online contexts (e.g. Bansal et al. 2010; Goldstein et al. 2008).

Personality traits

Personality traits can be defined as a "neuropsychic structure having the capacity to render many stimuli functionally equivalent, and to initiate and guide equivalent (meaningfully consistent) forms of adaptive and expressive behavior" (Allport 1961, p. 347). Several inventories have been developed to classify personality traits. The most prominent inventory is the Big Five Inventory (McCrae and John 1992) which distinguishes the personality traits of *extraversion*, *agreeableness*, *conscientiousness*, *neuroticism*, and *openness to experience*. The Big Five Inventory has been used in the past to advance IS theories (e.g. Junglas et al. 2008; Svendsen et al. 2013). So far, only few studies have examined personality traits in nudging (Jung and Mellers 2016; Stutzer et al. 2011). John and Srivastava (1999) provided comprehensible definitions for each trait.

Agreeableness "contrasts a prosocial and communal orientation towards others with antagonism and includes traits such as altruism, tender-mindedness, trust, and modesty" (John and Srivastava 1999, p. 30). Hence, individuals with high agreeableness are trustful, value communal goals and interpersonal harmony. Therefore, they are more likely to follow the social norm to act in line with communal goals and other individuals. This assumption is also supported by previous research which has shown that people with high agreeableness and conscientiousness are more likely to act in line with the social norms of their culture (Gebauer et al. 2014). Moreover, defaults work better on individuals with high agreeableness. This is due to the implicit recommendation effect which creates trust in the pre-selection. Therefore, individuals with high agreeableness are more prone to choose the defaulted product.

H4*: Digital nudges of the type default positively influence sustainable product choices for participants with high agreeableness.*

H5*: Digital nudges of the type social norms positively influence sustainable product choices for participants with high agreeableness.*

Neuroticism "contrasts emotional stability and even-temperedness with negative emotionality, such as feeling anxious, nervous, sad, and tense" (John and Srivastava 1999, p. 30). Consequently, neuroticism is associated with being anxious and nervous. For this reason, neurotic participants are particularly susceptible to warnings due to the risk and loss aversion effects that are triggered by warnings. In addition, neurotic individuals follow social norms because of their validating, implicit recommendation effect which responds to the neuroticism.

***H6**: Digital nudges of the type warnings positively influence sustainable product choices for participants with high neuroticism.*

***H7**: Digital nudges of the type social norm positively influence sustainable product choices for participants with high neuroticism.*

Conscientiousness "describes socially prescribed impulse control that facilitates task- and goal-directed behavior, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing, and prioritizing tasks" (John and Srivastava 1999, p. 30). Conscientious individuals value achievement, order, and efficiency, and are therefore susceptible to defaults which provide order and efficiency in the purchasing process.

***H8**: Digital nudges of the type default positively influence sustainable product choices for participants with high conscientiousness.*

Extraversion "implies an energetic approach toward the social and material world and includes traits such as sociability, activity, assertiveness, and positive emotionality" (John and Srivastava 1999, p. 30). Extraverts are especially sensitive to rewards and social attention. Therefore, social norms work better on participants with high extraversion.

***H9**: Digital nudges of the type social norm positively influence sustainable product choices for participants with high extraversion.*

Openness to experience "describes the breadth, depth, originality, and complexity of an individual's mental and experiential life" (John and Srivastava 1999, p. 30). We do not formulate a directed hypothesis for participants with high openness but study its effect exploratively. All hypotheses are depicted in the research model in Figure 19.

Research model

The hypotheses are embedded in the stimulus-organism-response (S-O-R) model (Mehrabian and Russell 1974).The S-O-R model presumes that stimuli affect the decisions of individuals when they are processed by the organism. The resulting actions are labelled the response (Mehrabian and Russell 1974). In our experiment design, the nudges serve as stimuli, while the organism is the moderating role of personality traits. Finally, the choice of products represents the response. We have chosen the S-O-R model because it has been widely applied in the context of online shopping (Pantano and Viassone 2015; Peng and Kim 2014).

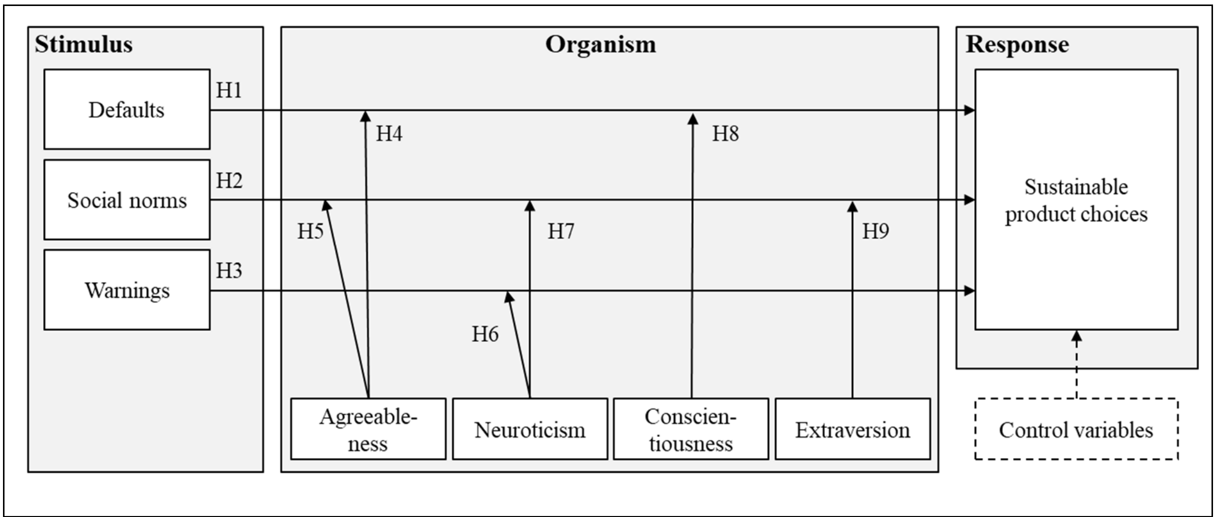

Figure 19. Research model

We conclude that, although nudges are very popular in a sustainability context and personality traits are established constructs in various settings, little research has been conducted at their intersection. Thus, it remains particularly unclear whether personality traits moderate the influence of different digital nudges. We address this issue with an online survey experiment which is illustrated in Chapter 4.2.3 below.

4.2.3 Research Methodology

Experiment design

To answer our research question, we conducted an online survey experiment in summer 2018. Survey experiments are established methods of data collection and combine the generalizability and external validity of surveys with the valid causal inference and the internal validity of experiments (Krosnick et al. 2014; McFadden et al. 2005). Moreover, several prior studies, that are similar to our design, have also used survey experiments (e.g. Aldrovandi et al. 2015; Baek et al. 2014; Momsen and Stoerk 2014). Our participants were part of a university pool which comprises mainly students of a mid-sized German city. The participants were invited by E-Mail to participate in the study, and they could win a voucher as a compensation for their participation. On average, each participant received a theoretical compensation of 9€ per hour, but in the end only 30 out of 452 participants were selected as winners of vouchers worth 40€ each.

The online survey experiment consists of an experimental part and a survey part. We developed the experimental part ourselves and hosted it as a website using Amazon Web Services. In this part, the participants were first introduced to the context. Thereby, they were informed that they had invited friends for a meal, and that they still had to buy several products. The six products (bananas, tomatoes, coffee, milk, pasta and bread) were pre-defined by a shopping list. Then, the participants were directed to a non-branded online grocery store where they informed themselves about the different products and chose between a sustainable or non-sustainable version of each product. Finally, the participants were forwarded to the online survey which was based on the established survey software “Unipark”. In this part, they filled out a survey with the different measurement items (see Appendix B for a full list of all items).

Treatments

The experiment was carried out as a between-subject design (List et al. 2011) and the participants were randomly assigned to the experimental groups based on a random number that was drawn in the beginning (Kirk 2003). Consequently, they were either assigned to one of the treatment groups, or to the control group. The participants were not aware of the different groups, but most participants recalled the treatment at the end of the survey. Importantly, we replicated existing and validated treatments. We have not developed new treatments within this study as we were interested in the interaction effects of digital nudges and personality traits. The different treatments were operationalized as follows (see Table 18).

Table 18. Overview of experimental treatments

Treatment	**#**	**Implementation**	**Source**
Default	1	Sustainable product is preselected	Campbell-Arvai et al. (2014); Theotokis and Manganari (2015)
Social norms	2	Display: “For your information, 70% of the previous participants purchased at least three sustainable products”	Demarque et al. (2015)
Warnings	3	Display red traffic-light next to conventional product and display green traffic-light next to sustainable product	Thorndike et al. (2012); Thorndike et al. (2014)
Control	4	No preselection or message	n/a

The default was implemented by pre-selecting each sustainable product, the social norms by permanently displaying a social norm message above the products, and the warnings by displaying different traffic-lights next to the products. The control group received the same interface, but without the default nudge, or any message. Screenshots of the user interfaces can be found in Appendix E.

Measurements

The dependent variable is represented by the binary choice of whether the sustainable product was chosen or not. For reasons of clarity, the absolute or average number of sustainable products chosen is occasionally reported as the dependent variable in the descriptive results. The independent variables are the three different treatments of default, social norms, and warnings. The personality traits are based on the Big Five Inventory using the 42-item questionnaire (John and Srivastava 1999; Lang et al. 2001). In addition, we measured the acceptance of nudges, hereafter referred to as “policy agreements”, using the measurements of Reisch and Sunstein (2016). To control for various other effects, we also measured the constructs from the theory of planned behavior (Ajzen 1991), such as attitudes, trust, purchase intentions, and subjective norms (all items from Teng and Wang 2015). Further we assessed for environmental knowledge (Mostafa 2007), whether the participants normally consume the different products and how often they purchase the respective products sustainably. All items were measured using a seven-point Likert scale, except for acceptance of nudges (approve/disapprove) and usual consumption (yes/no). We also included manipulation checks by asking whether any product has been pre-selected, whether a message was displayed on the product page, or whether any products were displayed along with a traffic-light. If so, then the participants had to indicate which products were pre-selected or describe the message or traffic-light. Finally, we assess the demographics of the participants and their daily Internet usage (including mobile Internet usage).

Data analysis

The data is analyzed using a logistic regression model as we aim to predict a binary dependent variable (sustainable product yes/no) with several continuous and categorical independent variables. Before running the regression model, we transform the data to a long format with as many lines as we have product choices (2,712 product choices in total). Thereby, we use z-transformed scores to make the values of the different personality traits comparable. At the same time, we control for the different products, the participant ID and an error term. The main regression equation (including moderating effects) can be described as follows:

$$Pr(Choice_i = 1) = \beta_0 + \beta_1 \cdot treatment_j + \beta_2 \cdot extraversion_i + \beta_3 \cdot openness_i + \beta_4 \cdot agreeableness_i + \beta_5 \cdot conscientiousness_i + \beta_6 \cdot neuroticism_i + \beta_7 \cdot treatment_j \cdot extraversion_i + \beta_8 \cdot treatment_j \cdot openness_i + \beta_9 \cdot treatment_j \cdot agreeableness_i + \beta_{10} \cdot treatment_j \cdot conscientiousness_i + \beta_{11} \cdot treatment_j \cdot neuroticism_i + \beta_{12} \cdot product_i + \beta_{13} \cdot ID_i + error_0$$

where *Pr(Choice)* determines the probability of selecting a sustainable product, *i* indexes the participant, *j* indexes the treatment (whereas each participant receives the same treatment across all products), while the *βs* denote the regression estimators of the respective direct and interaction effects. *Product* controls for the different product categories with separate binary dummy variables while *ID* controls for the participants. Finally, we added an error term. To estimate the main effects of the digital nudges, we use the statistical programming language “R” and the respective integrated development environment “RStudio” (version 1.0.143).

In addition to the logistic regression model, we additionally calculated a mixed-effects logistic regression model as we had several observations for each participant. This model controls for the problems of dependencies that arise if each interaction of the digital nudge with the personality traits would be estimated separately. Mixed effects logistic regression models are occasionally used in digital nudging studies (e.g. Tietz et al. 2016; Weinmann et al. 2017). To solve the regression equation, we use particularly the “lme4” package within R which contains mixed effects logistic regression models.

Pre-tests

We conducted several pre-tests prior to the main study. Firstly, we pre-tested the labels of the sustainable products as several popular labels exist in Germany. Thereby, we presented three alternatives to the participants: several products with the bio label of the European Union (EU), several products with the German bio label, and several products without any label. For reasons of simplicity, we stayed with the dimension of organic products, and did not enter the discussion that sustainability can also be comprised of fair trade, local production, carbon emissions, etc. The participants rated the products in terms of appeal, trustworthiness, and sustainability on a seven-point Likert scale. The results revealed that the participants of the pre-test perceived the products with the labels as equally appealing, but as less trustworthy and sustainable compared with the unlabeled products. The differences between the two labels were marginal. Hence, we decided to use the German bio label as the main study was conducted in Germany, too.

Secondly, we assessed the external validity and the complexity of the setting by conducting walkthroughs with six individuals using the think-aloud protocol. This ensured the applicability of the experimental design. Thirdly, we conducted an online survey experiment with 239 participants in April 2018 using only four products (bananas, tomatoes, coffee, milk), only the default treatment, and measuring the personality trait of conscientiousness. The participants were recruited from the same university pool, but we ensured that the participants of the pre-study could not join the main study. In this pre-study, we found first evidence for interaction effects between the digital nudge and the individual characteristics of conscientiousness. Hence, we conducted a large-scale study in a second step.

4.2.4 Results

Descriptive results of the main study

The main study was conducted in June 2018 with 452 participants. It took about 15-20 minutes in total to complete the experiment and the survey. With an average age of 24 years, our participants were younger than the average German Internet population (Statista 2018). We had a more male sample (63%), and the sample was highly educated with 48% of the individuals having a high school degree and 46% at least a university degree. Finally, the participants reported an average daily Internet usage (including mobile Internet usage) of 5.2 hours. Although our sample is not representative, the demographics are similar to previous studies in terms of age and gender distribution (compare Demarque et al. 2015; Theotokis and Manganari 2015). In line with these authors, we argue that the results can, in principle, "be applied to all consumer populations that use a particular shop or website" (Demarque et al. 2015, p. 172). Moreover, students represent the generation with a high affinity towards online shopping environments, and which is aware of the topic of sustainability (Campbell-Arvai et al. 2014).

Before depicting the product choices, we provide an overview of the Big Five personality traits. Table 19 shows that the sample has a similar degree of agreeableness, conscientiousness, extraversion and openness, but is less neurotic. The results for the Big Five Inventory are similar to other studies (e.g. Lang et al. 2001).

Table 19. Overview of personality traits

Personality trait	**Items**	**Mean**	**SD**	**Observations**	**Source**
Agreeableness	8	4.8	0.7	452	Lang et al. (2001); McCrae and John (1992)
Neuroticism	7	3.5	0.9	452	
Conscientiousness	9	4.9	0.7	452	
Extraversion	8	4.7	1.0	452	
Openness	10	4.9	0.7	452	

In total 2,712 choices were made (452 participants with 6 product decisions each). Thereof, the sustainable product was chosen in 60.7% of the cases. However, the choices are different for each product. While sustainable bananas were chosen with a rate of 59%, sustainable tomatoes with 67%, sustainable milk with 54%, and sustainable coffee with 60%, it was less common to buy sustainable pasta (37%) or sustainable bread (45%).

Next, we analyzed the choices of the different treatment groups (see Figure 20). Thereby, it became clear that the average number of sustainable products diverged heavily between the treatment groups. While the control group chose 3.4 sustainable products on average, the group with social norms only chose 2.9 (-16%) sustainable products, the group with a warning message chose 3.6 (+5%) sustainable products, and the default group chose 4.5 (+32%) sustainable products. It is also apparent from Figure 20 that the median for the group with social norms and the control group are similar, but that the interquartile ranges (IQR) for the control group and the warnings group are much larger than for the groups that received defaults or social norms.

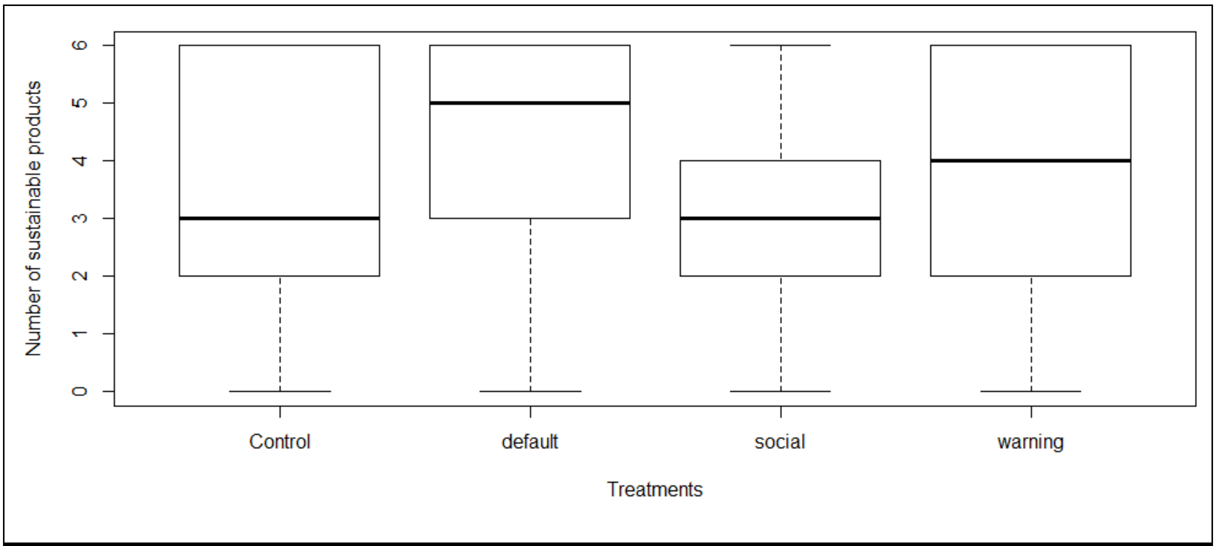

Figure 20. Boxplot of number of sustainable products chosen per treatment group

Moreover, we can be sufficiently sure that these differences can be traced back to our treatments. When evaluating the data on manipulation checks, we found that about 75% of the participants were able to correctly recall their treatment (i.e. that products had been pre-selected, that a message was displayed or that the products were displayed along with a traffic-light). We consider this a high value since the manipulation checks were among the last items of the survey and occurred about 10-15 minutes after the treatment which is at the upper level of the short-term memory.

Statistical hypothesis testing of main effects

At first, we tested the direct effects of the digital nudges on the choice of sustainable products, leaving out the individual characteristics initially. The results of this logistic regression model are displayed in Table 20 below. They suggest that defaults are significant at the 0.1%-level ($p<0.001$), social norms are significant at the 1%-level ($p<0.01$), while warnings are insignificant (p-value of 0.28). Interestingly, defaults lead to a significant increase in the number of sustainable products selected, whereas social norms reduced the number of sustainable products selected. Most product categories (except for milk) are significantly different from the reference category (bananas). Hence, we confirm hypothesis H1 and we reject H3. H2 is statistically significant but in the opposite direction than expected.

Table 20. Regression output of logistic regression model of main treatment effects

Treatment	**Estimate**	**Std. error**	**T value**	**P-value**
Intercept	0.5509	0.1427	3.860	**p<0.001*** **
Default	0.8673	0.1221	7.101	**p<0.001*** **
Social norms	-0.3834	0.1197	-3.204	**0.0014** **
Warnings	0.1158	0.1082	1.071	0.2843

Product category bread	-0.6058	0.1398	-4.333	**p<0.001*** **
Product category coffee	-0.2481	0.1411	-1.758	**0.0787(.)**
Product category milk	0.1148	0.1445	0.794	0.4270
Product category pasta	-1.0630	0.1410	-7.542	**p<0.001*** **
Product category tomatoes	0.4432	0.1497	2.960	**0.0031** **
ID	0.0001	0.0003	-0.252	0.8013
AIC	3,408.6			
Observations / ids	2,712 / 452			
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '(.)' 0.1; product category bananas serves as the reference category for the other product categories				

Next, we estimated the interaction effects which were based on the main regression equation depicted earlier in the data analysis section. In a final step, we further examined the main and interaction effects with respect to the control variables.

Statistical hypothesis testing of interaction effects

To estimate the interaction effects, the Big Five personality traits are added to the regression equation, and they are multiplied with the treatments. The results are shown in Table 21.

Table 21. Regression output of logistic regression model including personality traits

Treatment	**Category**	**Estimate**	**Std. error**	**T value**	**P-value**
Intercept	Intercept	0.5073	0.1460	3.475	**p<0.001*** **
Default	Treatment	0.8395	0.1251	6.708	**p<0.001*** **
Social norms		-0.3692	0.1222	-3.021	**0.0025** **
Warnings		0.1453	0.1110	1.309	0.1906
Extraversion	Personality	-0.0163	0.0898	-0.182	0.8559
Openness		-0.1410	0.0904	-1.560	0.1187
Agreeableness		0.1806	0.0821	2.200	**0.0278***
Conscientiousness		0.1831	0.0798	2.293	**0.0218***
Neuroticism		0.1081	0.0833	1.298	0.1944
Default x Extraversion	Interaction	-0.2629	0.1472	-1.786	**0.0741(.)**
Social norms x Extraversion		0.0120	0.1298	0.092	0.9265
Warnings x Extraversion		0.0592	0.1244	0.476	0.6342
Default x Openness		0.3976	0.1425	2.790	**0.0053** **
Social norms x Openness		0.1169	0.1297	0.901	0.3674
Warnings x Openness		0.1943	0.1194	1.627	0.1037
Default x Agreeableness		-0.0354	0.1355	-0.261	0.7939
Social norms x Agreeableness		-0.1455	0.1234	-1.179	0.2384

Warnings x Agreeableness		0.0433	0.1182	0.366	0.7141
Default x Conscientiousness		0.1534	0.1347	1.139	0.2547
Social norms x Conscientiousness		-0.2021	0.1257	-1.608	0.1079
Warnings x Conscientiousness		-0.3159	0.1159	-2.725	**0.0064****
Default x Neuroticism		-0.0617	0.1367	-0.452	0.6516
Social x Neuroticism		-0.1646	0.1242	-1.325	0.1851
Warnings x Neuroticism		-0.0512	0.1194	-0.429	0.6681
Product category bread	Product categories	-0.6167	0.1411	-4.372	**p<0.001*****
Product category coffee		-0.2522	0.1423	-1.773	**0.0763(.)**
Product category milk		0.1166	0.1456	0.800	0.4235
Product category pasta		-1.084	0.1424	-7.611	**p<0.001*****
Product category tomatoes		0.4493	0.1508	2.980	**0.0029****
ID	id	0.0001	0.0004	0.221	0.8248
AIC	3,400.5				
Observations / ids	2,712 / 452				
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '(.)' 0.1; product category bananas serves as the reference category for the other product categories					

The results of the regression model yield that defaults remain significant at the 0.1%-level (p<0.001), social norms remain significant at the 1%-level, while warnings remain insignificant. Concerning the interaction effects, there are two significant interactions and one marginally significant interaction between the digital nudges and the personality traits. Firstly, defaults interact positively with openness (p<0.01)**.** This implies that defaults work better on participants with high levels of openness and worse on participants with low levels of openness compared with the control group. Secondly, warnings interact negatively with conscientiousness (p<0.01). In contrast, this means that warnings work better on participants with low levels of conscientiousness and worse on participants with medium or high levels of conscientiousness compared with the control group. The results of the interaction effects are also reflected in the trend lines of Figure 21. Moreover, we find a marginally significant interaction effect. Thereby, default and extraversion show a negative interaction (p-value of 0.07). Finally, two interaction effects (warnings and openness as well as social norms and conscientiousness) have a similar strength as the interaction of default and extraversion, but they are not marginally significant anymore with p-values of 0.10 und 0.11. Hence, we have to reject hypotheses H4-H9, but we find other interaction effects instead.

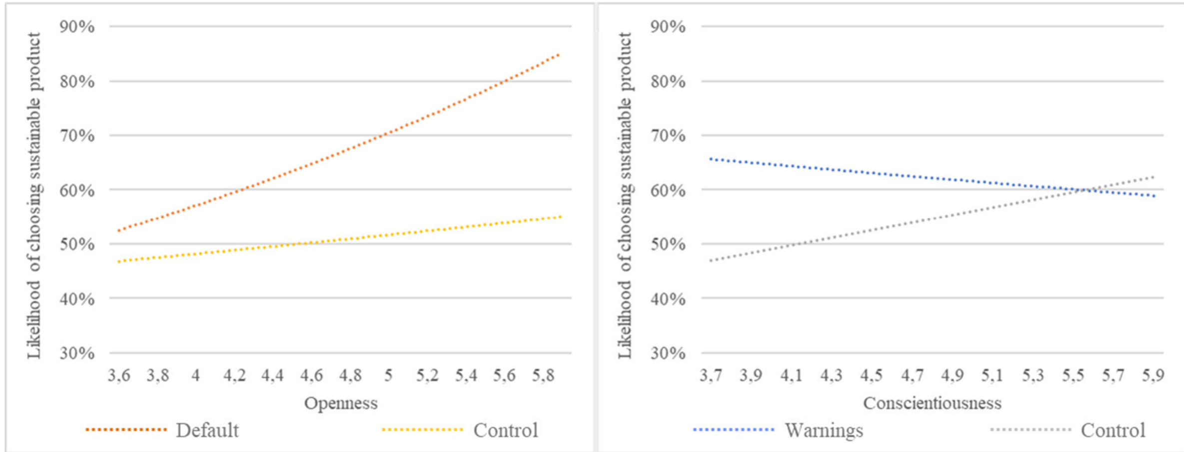

Figure 21. Interaction effects of defaults and openness and warnings and conscientiousness

Statistical hypothesis testing of main and interaction effects with control variables

To test the robustness of the results, we performed additional calculations and we include further control variables. As part of the additional calculations we ran a mixed-effects logistic regression model to control for the potential missing independence of residuals. Thereby, we find for the direct effects that defaults are significant at the 0.1%-level, that social norms are only significant at the 10%-level (p-value of 0.06), and that warnings remain insignificant (p-value of 0.65). When including the moderating effects of personality traits, the results of the direct effects only change marginally. However, the interaction effects of defaults and openness as well as of warnings and conscientiousness are now only significant at the 10%-level. The full results of the mixed-effects logistic regression models are displayed in Appendix C.

To estimate which control variables might be effective, we created a correlation matrix (see Table 22). Hence, we tested for demographics, Internet usage, purchase intentions, attitude, trust, subjective norms, knowledge, policy agreement, consumption, and purchase frequency as these constructs correlated to some degree with the dependent variable. Firstly, the results on an overall level remain stable when *demographics* are added as control variables. Only including Internet usage (which itself has a significant influence on the dependent variable) slightly reduces the interaction effect of defaults and openness. The constructs from the theory of planned behavior (*purchase intentions, attitude, trust and subjective norms*) are all significantly related to the dependent variable (see also Table 22). Including them as control variables reduces the magnitude of the direct effects such that social norms turn insignificant. In addition, these constructs reduce the interaction effect of default and openness but mostly not the interaction effect of warnings and conscientiousness. Interestingly, when including trust as a control variable, the interaction effect of social norms and conscientiousness turns significant. Moreover, when including subjective norms as control variables, the direct effect of warnings on sustainable product choices turns significant. The remaining control variables (*knowledge, policy agreement, consumption and purchase frequency*) had diverse effects and vary between decreasing and increasing the magnitude of the direct and interaction effects. While they are all significantly related to the dependent variable, they mostly reduce the interaction effects without impacting the direct effects of the treatments. However, including consumption significantly increases the interaction effect of warnings and openness. Moreover, when including purchase frequency, the interaction effect of social norms and extraversion turns significant.

To conclude, the effects of defaults and the interaction effect of warnings and conscientiousness are robust despite multiple control variables, while the effect of social norms and defaults and openness mostly turn insignificant when control variables are included in the regression equation. In addition, we note that some control variables strengthen various other interaction effects.

To sum up the results, we conclude that digital nudges can have a positive as well as a negative impact on sustainable product choices. Moreover, certain interaction effects exist between different digital nudges and personality traits. In particular, defaults interact positively with openness, while warnings interact negatively with conscientiousness. Finally, these results are discussed in Chapter 4.2.5.

Table 22. Inter-construct correlation matrix

#	Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Sust. product choice	1.00																
2	Extraversion	0.00	1.00															
3	Agreeableness	0.11	0.16	1.00														
4	Conscientiousness	0.08	0.26	0.22	1.00													
5	Neuroticism	0.02	-0.24	-0.21	-0.13	1.00												
6	Openness	0.04	0.29	0.09	0.27	-0.13	1.00											
7	Intention	0.57	0.07	0.13	0.13	-0.02	0.13	1.00										
8	Attitude	0.37	0.14	0.11	0.10	0.00	0.12	0.51	1.00									
9	Trust	0.26	0.03	0.19	0.07	-0.03	0.11	0.36	0.44	1.00								
10	Norm	0.31	0.12	0.09	0.05	-0.02	0.08	0.46	0.37	0.32	1.00							
11	Knowledge	0.18	0.23	0.14	0.17	-0.07	0.28	0.39	0.23	0.14	0.23	1.00						
12	Policy agreement	0.15	0.17	0.12	0.07	0.07	0.14	0.26	0.28	0.14	0.24	0.11	1.00					
13	Gender	0.02	0.14	0.07	0.17	0.28	0.00	0.16	0.07	0.03	0.05	0.03	0.17	1.00				
14	Age	0.01	-0.08	-0.04	0.04	0.01	0.07	0.10	0.04	-0.03	-0.03	0.04	-0.06	0.04	1.00			
15	Education	-0.04	0.02	0.02	0.13	-0.05	0.06	0.08	0.00	0.06	0.07	0.18	0.00	0.05	0.30	1.00		
16	Income	-0.08	0.03	-0.09	0.05	-0.02	0.08	-0.10	-0.03	-0.12	-0.11	0.03	0.03	-0.04	0.06	0.09	1.00	
17	Internet usage	-0.05	-0.02	0.04	-0.11	0.03	0.02	-0.02	-0.06	-0.03	0.00	-0.04	0.01	0.00	0.01	-0.01	-0.03	1.00

4.2.5 Discussion

Sustainability is a key issue of our time and past research has shown that consumers often fail to behave as intended when facing a choice between sustainable and unsustainable products. Based on user-interface design elements, so-called digital nudges, this study aimed to nudge consumer choices in digital environments to ultimately increase the consumption of sustainable products under the consideration of personality traits. The results can be discussed in three ways:

Firstly, the results show diverging effects of the digital nudging treatments on sustainable product choices. Defaults were able to significantly increase the choice of sustainable products on average by more than one product or about 32%. This change is in line with other studies using defaults (e.g. Steffel et al. 2016; Theotokis and Manganari 2015). Apparently, switching away from a pre-selected choice puts a burden on consumers which has been shown before in several studies in an environmental context (e.g. Campbell-Arvai et al. 2014; Hedlin and Sunstein 2016; Theotokis and Manganari 2015). Interestingly, digital nudges using social norms can also lead to backfire effects and reduced the number of sustainable products chosen on average by more than 0.5 products or -16%. We hypothesize that participants might have interpreted the slogan "*For your information, 70% of the previous participants purchased at least three sustainable products*" in a way that many sustainable products have already been bought by other participants before. Therefore, their own contribution might not matter that much anymore which reduced the willingness to choose sustainable products. This effect can occur when the reference value is too high. Moreover, the slogan referenced "three sustainable products", which might have created an anchor. Indeed, most participants in this group (26%) have selected exactly three sustainable products. This anchor might have been too low compared with the control group as 50% of the participants in the control group have chosen more than 3 products. This effect can occur when the reference value is too low. Hence, the exact formulation of the social norm or reference value needs to be chosen carefully. Nevertheless, these results are in line with other social norms that produced contrary effects (e.g. Liu et al. 2016). We conclude that, when selecting a digital nudge, the choice architect (Thaler and Sunstein 2008) not only has to consider the target group, but also the ease of construction of the digital nudge. While defaults are easy to design, social norms require a priori knowledge about the expected consumer behavior to avoid backfire effects (Schultz et al. 2007). The warnings treatment had no effect although they were very effective in conventional settings (e.g. Cioffi et al. 2015; Thorndike et al. 2012). This finding shows that nudges from offline environments cannot be simply transferred to digital environments.

Secondly, we conclude that individual characteristics, particularly personality traits, can diminish or reinforce the effect of digital nudges. On an overall level, we found significant interactions of defaults and openness (positive interaction) as well as warnings and conscientiousness (negative interaction). Participants with an increasing degree of openness chose slightly more sustainable products in the control group but many more sustainable products in the treatment (default) group. One reason for this finding might be that participants with high openness are in principle willing to try new things and to purchase sustainable products, but they need an extra push in the right direction which is provided by the digital nudge. On the contrary, participants with low openness are less willing to try something new in the first place, and they are therefore also hardly impacted by the digital nudge. The positive correlation of openness and sustainable product choices is in line with previous research (Luchs and Mooradian 2012). Opposite conclusions can be drawn for the negative interaction of warnings and conscientiousness. Thereby, the control group chose more sustainable products with increasing levels of conscientiousness which is also in line with previous research (Luchs and Mooradian 2012). Participants who had received a warning, chose more (less) sustainable products for low (high) levels of conscientiousness. We assume that participants with high conscientiousness focused on completing the shopping task efficiently and were less distracted or influenced by the warning. In contrast, participants with low conscientiousness are more disorganized, careless and less efficient and they were focusing more on the warning of not purchasing unsustainable products. This finding could be verified by a follow-up study using eye-tracking technology. Some interactions, that were hypothesized, could not be confirmed. We presumed for instance that the efficiency focus of individuals with high conscientiousness would lead to choosing the faster option (i.e. staying with the default). This did not seem to be true. In addition, defaults and social norms were independent of the degree of agreeableness of the participant. We can only speculate why this is the case, for instance because other predictors were more important. Given the low average and variance of neuroticism in our sample, no interaction effects were found for neuroticism.

Thirdly, the results remained fairly stable when various control variables were added. Particularly the constructs from the theory of planned behavior (Ajzen 1991) had a significant influence on the choice of sustainable products. These results are in line with previous studies in the realm of sustainable consumption (e.g. Teng and Wang 2015), but raise the question whether behavior or intentions were measured by the choices in this experiment. Moreover, we conclude that the direct effect of defaults as well as the interaction effect of warnings and conscientiousness remained significant even when various control variables were added. As a consequence, this constitutes an important and reliable basis for future studies in this area. Interestingly, the direct effect of warnings is strengthened by subjective norms while various interaction effects turn significant when including trust, consumption or purchase frequency. In addition, it is noteworthy that the results were heterogeneous for the respective product categories. While for some products the interaction effects are very pronounced, they are insignificant for the other products. Hence, we conclude that there are not only personality-dependent moderation effects but also product-dependent moderation effects. We assume that the risk or trust involved with the product category might make a difference as nudges are more effective when the decision is infrequent or complex (Thaler and Sunstein 2008). Yet, we were not able to test for such effects as all sustainable products in our online shop were from the same product category of food items. Finally, we also presented the results from a mixed-effects logistic regression model which attenuate the results of social norms (marginally significant) and of the interaction effects (marginally significant, too).

4.2.6 CONCLUSION

Increasing the choice of sustainable products benefits consumers, suppliers and the environment. Tools of choice architecture can help to reach those benefits, especially in digital environments. This study tested different digital nudging treatments and found that defaults (social norms) increase (decrease) the choice of sustainable products compared with the control group. Moreover, the effects are moderated by personality traits such that defaults interact positively with openness and warnings interact negatively with conscientiousness.

We contribute to existing IS research in several ways. Firstly, our study contributes empirically to the emerging field of digital nudging. It offers one of the first digital nudging studies that tests different digital nudges against each other. Thereby, it is a valuable finding that digital nudges can do both harm and good. Secondly, we show that these effects are reinforced or diminished dependent on the personality traits. As far as we know, this moderating effect has been proposed theoretically (e.g. Goldstein et al. 2008; Halpern 2016; Johnson et al. 2012), but, up to now, not verified empirically.

Practitioners of different professions can use our results. Designers of digital channels are now able to design individualized digital channels that match the personality of the consumer. As the personality can easily be determined, e.g. based on social media data (Markovikj et al. 2013; Youyou et al. 2015), providers of digital channels can increase the conversion rate with the respective digital nudges. Alternatively, individuals could deliberately make their personality traits available to receive certain benefits. This is similar to other personal data that is shared today in exchange for benefits or rewards. In addition, providers of online channels could pre-select sustainable products in line with legal and ethical standards (von Grafenstein et al. 2018). Policy makers can implement the findings in tailoring environmentally friendly policies, for example by rather using defaults than social norms to promote sustainable consumption. In practice, this could be achieved by requiring airlines and booking platforms for flights to charge consumers automatically a specific amount to offset their emissions whereas (Reisch and Sunstein 2016). This helps governments to reach environmental goals, or the international community to achieve the SDG #12 of the UN on responsible consumption and production (United Nations 2018).

Nevertheless, the proposed study has some limitations. For instance, we left out the question of pricing which limits the external validity of the findings. This has been done deliberately as student-dominated samples are known to be price sensitive which would have distorted the results. Moreover, including prices and incentives would imply that the participants bear the consequences of higher-priced sustainable products without receiving the benefits (health, regional production, etc.) of them. In turn, most students are aware that sustainable products are more expensive and might have included this knowledge subconsciously in their decision. Another limitation is the use of the participant pool of the local university which is dominated by students. Therefore, the sample is not representative for the German Internet population. However, we describe in Chapter 4.2.4 why this does not limit the conclusions that can be drawn from the research. Finally, we used a narrow definition of sustainability focusing on organic products using the German bio label. Potentially, consumers are also influenced by other dimensions of sustainability such as fair trade, local production or carbon emissions.

Future research could experiment with different wordings of the social norm (similar to Demarque et al. 2015) to test whether the anchoring effect reoccurs. In addition, different nudges presented by Sunstein (2014) could be used, e.g. increasing ease and convenience, or using pre-commitment strategies. Further, combining the digital nudges with an eye-tracking elaboration might further enhance the treatment effects (compare Hummel, Toreini, et al. 2018), and verify whether participants with low conscientiousness were focusing more on the warning than participants with high conscientiousness. Moreover, the breadth of individual differences is endless so that other constructs can be tested for their interaction effects. Also, the question of product dependency leaves the issue whether nudges interact differently with individual characteristics when non-food items are concerned. Finally, it is promising to test whether the results can be replicated with a representative sample that has enough statistical power to further strengthen the interaction effects or to find new ones.

5 Discussion

This thesis concludes with a discussion of the results of all four studies. The overall discussion (Chapter 5.1) is followed by contributions to theory (Chapter 5.2) and to practice (Chapter 5.3) as well as the limitations (Chapter 5.4), an outlook on future research (Chapter 5.5) and some concluding remarks (Chapter 5.6).

5.1 Overall Discussion

We started from the notion that new retail channels have arisen from technological innovation. Despite new opportunities for consumers and providers, few consumers rely exclusively on digital channels (Sopadjieva et al. 2017). One reason for this resistance might be the lack of individualization of digital channels according to the individual consumer characteristics. Related IS research has shown that individualized UIs are able to positively influence various dependent variables, such as online contribution, online participation or technology usage (Nov, Arazy, López, et al. 2013; Nov, Arazy, Lotts, et al. 2013; Oulasvirta and Blom 2008). Consequently, this thesis studies how channel characteristics relate to individual characteristics. Furthermore, we analyze the potential impact on channel choices and sustainable product choices. Across four studies, the thesis (1) classifies the determinants of multi-channel behavior, (2) analyzes how individual characteristics antecede channel characteristics, (3) conceptualizes empirical nudging studies and determines their effectiveness, and (4) tests different digital nudges against each other to uncover interaction effects of digital nudges and personality traits.

The results of Study 1 show that channel choices are influenced by a large variety of determinants that can be clustered into four dimensions: channel, context, consumer and product. These clusters integrate well into existing research (Neslin et al. 2006; Trenz and Veit 2015). For example, Trenz and Veit (2015) categorize the determinants into similar groups (channel determinants, purchase specifics, external influences, and individual differences). However, previous studies have not provided a conceptualized framework (e.g. a taxonomy or morphological box) which allows for a consistent classification and comparison of the determinants of multi-channel behavior. In addition to this conceptualization, counting the frequency of occurrence of each characteristic unveils differences in the research coverage, especially between products and services. Subsequently, exemplary research questions for future research are derived from gaps in the research coverage of services. These research questions are:

1. How does a channel's capability for social interaction affect consumers' channel choice in the service industry?
2. How does channel and firm loyalty affect consumers' channel choice in the service industry?
3. How is channel choice moderated by different service categories of financial services?

Building on these findings, Study 2 examines the connections of two dimensions of the morphological box from Study 1. Based on an existing model (Kim et al. 2008), it detects that personality traits and gender roles are antecedents of perceived risk, trust and perceived benefits. While earlier studies examined the interplay between personality traits in online environments (e.g. Bansal et al. 2010; Turkyilmaz et al. 2015), personality traits and gender roles have never been found to antecede these constructs. Moreover, the original model of Kim et al. (2008) is replicated in an experimental context which is a valuable response to the replication crisis (Erdfelder 2018). The findings can be used among others for an individualization of digital channels.

It can be concluded from Study 1 and 2 that not only the characteristics of digital channels matter but also the individual consumer characteristics. Or to express it with the words of the (famous) personality psychologist Orval Hobart Mowrer: “To understand or predict what a rat will learn to do in a maze, one has to know both the rat and the maze“ (Mowrer 1960, p. 10).

While the first two studies focus on descriptive knowledge and leave little scope to explore how providers could influence consumer behavior, the concepts of nudging and digital nudging (Thaler and Sunstein 2008; Weinmann et al. 2016) are used for Studies 3 and 4. Study 3 lays the foundation and illustrates the effect sizes of different nudges. The results are discussed along the dimensions of the morphological box of empirical nudging studies (Figure 13). It is particularly noteworthy that only 63% of all nudges resulted in a significant change of the dependent variable. We hypothesize that this might be explained in part by moderating effects. Study 3 already provides a first glance at the occurrence of such effects, e.g. the moderating effect of age in emotive warning messages (Esposito et al. 2017). Study 3 concludes with avenues for future research in digital nudging for the IS community.

The findings of Study 3 are picked up in the final study which shows empirically that digital nudges can have positive as well as negative (i.e. backfire) effects. Moreover, Study 4 supports the idea of interaction effects of digital nudges with personality traits, e.g. defaults interact positively with openness. Hence, we provide evidence that not only the (digital) nudge itself matters, but also the personality traits of the decision-makers. The findings can be linked with the IS research identity from the first chapter that the interplay between digital channels (“IT Artifact”) and individual characteristics (“Individuals”) matter (Sidorova et al. 2008).

As the nudging concept is not free of criticism (Goodwin 2012; Hansen and Jespersen 2013; Johnson et al. 2012; Selinger and Whyte 2011), a short ethical discussion of the concept is needed. Researchers argue that many nudges represent a manipulation of the choice (Hansen and Jespersen 2013) and they can be misused, for example by the private sector (Abdukadirov 2016). Although Study 4 of this thesis was dedicated to a benevolent purpose (sustainability), the results could also be used by regular private companies to increase sales and profits. Despite regulatory barriers, e.g. limited possibility to use defaults, this would not be in line with the definition of nudging which should be in the interest of the decision-maker (Thaler and Sunstein 2008). Maybe this is why the concept is still under constant debate, despite its widespread success. Exemplarily for this debate, one of the authors of the book "Nudge: Improving Decisions About Health, Wealth, and Happiness", Richard Thaler, accepts that there is "Much Ado About Nudging" (Thaler 2017). In his paper, he responded directly to a paper by Loewenstein and Chater (2017) and acknowledges that nudging cannot solve all societal problems, and that policy makers should continue to use all the tools of social sciences (Thaler 2017). Moreover, his co-author, Cass Sunstein, also published a research paper on misconceptions about nudges and corrects six common misconceptions (Sunstein 2018). We also refer to a book on the ethics of influence for a further discussion (Sunstein 2016).

To summarize the overall discussion, channel characteristics interact with individual characteristics. Designers of digital channels can use these findings to individualize digital channels, to influence different outcome variables and to ultimately increase the use of digital channels.

5.2 Contributions to Theory

Overall, this thesis contributes in various ways to contemporary research in information systems and marketing. To classify the contributions, we rely on the taxonomy of theory types in Information Systems research (Gregor 2006, 2017), which defines five theory types: Analysis, Explanation, Predicting, Explaining and Predicting, and Design and Action. Table 23 below provides an overview of the theoretical contributions of each study.

Table 23. Theoretical contributions according to theory type

Study	Theory type	Main contribution
1	Analysis	• Conceptualization of determinants of multi-channel behavior along the dimensions of channel, context, consumer and product • Quantitative comparison of research coverage in products and services • Formulation of research gaps for future research
2	Explaining and Predicting	• Personality traits and gender roles are antecedents of perceived risk, trust and perceived benefits, e.g. agreeableness is positively related to trust while neuroticism is negatively related to perceived benefits • Replication of existing decision-making model (Kim et al. 2008)
3	Analysis; Explanation	• Morphological box on nudging with eight dimensions • Nudges have a median effect size of 21% which is influenced, among others, by the category and the context of the nudge • Possible moderation effects of individual characteristics • Avenues for future research in digital nudging for the IS community

4	Explaining and Predicting	• Defaults significantly increase sustainable product choices while social norms significantly decrease sustainable product choices • Effects of digital nudges are moderated by personality traits, e.g. defaults interact positively with openness
Note: Study 1 and Study 2 are summarized under the umbrella term of *individualized channel choices* (Chapter 3) while Study 3 and Study 4 are integrated in *nudging consumer choices* (Chapter 4)		

In the realm of *individualized channel choices* (Study 1 and 2), this thesis makes a contribution to an Analysis theory type (Study 1) and an Explaining and Predicting theory type (Study 2).

Study 1 provides a comprehensive conceptualization of determinants of multi-channel behavior by means of a morphological box. Thereby, it illustrates conceptually, which characteristics of the morphological box influence which channel choices. In addition, it highlights under-researched areas and provides avenues for future research in the services industry. It corresponds to an Analysis theory type as it "says what is" and provides no causal relationship but employs a type of classification, schema, framework or taxonomy (Gregor 2006).

Although other researchers have listed determinants of multi-channel behavior before (Neslin et al. 2006; Trenz 2015; Trenz and Veit 2015), they have not integrated them into a comprehensive framework. Only such a framework, as was presented in the morphological box in Chapter 3.1, allows for a consistent classification and comparison of the determinants of multi-channel behavior. Finally, the counting analysis and the resulting avenues for future research are a contribution of their own. To support this statement, research question 3 in Chapter 3.1.5 (how channel choice is moderated by different product categories of financial services. e.g. savings and investments) was subsequently answered in a separate publication by Hummel et al. (2017b).

Study 2 contributes to existing research by an Explaining and Predicting theory type which is characterized by testable propositions, causal explanations and is the most common type in information systems (Gregor 2006). First, it extends the theoretical model of Kim et al. (2008) and shows how personality traits, gender roles and channel characteristics are connected. These connections are based on testable propositions, and they predict how individuals with different personality traits and gender roles will behave in digital channels. In particular, it highlights that in the digital era it does not suffice to design channels in an isolated manner. Instead, the interaction effects with the individual consumer characteristics have to be always considered. In addition, the original model (Kim et al. 2008) was replicated which counters the claim of a replication crisis (Erdfelder 2018). Thereby, it provides testable propositions and causal explanations (Gregor 2006).

Where *nudging consumer choices* (Study 3 and 4) is concerned, this thesis makes a contribution to an Analysis as well as an Explanation theory type (Study 3) and an Explaining and Predicting theory type (Study 4).

Study 3 provides a contribution to the literature of behavioral economics and information systems. The knowledge of behavioral economics is advanced as most research has highlighted the effectiveness of nudging (Benartzi et al. 2017; Sunstein 2018; Thaler and Sunstein 2008) and its superiority to traditional interventions, such as financial incentives, or educational programs (Benartzi et al. 2017). Only selectively, researchers focused on the ineffectiveness of nudging (Sunstein 2017). Study 3 provides an empirical base for these opposing positions by showing that only 63% of the nudges included in the quantitative literature review resulted in a statistically significant outcome. These statistically significant outcomes are also related to the nudge category. For example, defaults are more effective than other nudges such as precommitment strategies or reminders. The results are in line with previous studies that have shown a higher effectiveness of defaults (e.g. Campbell-Arvai et al. 2014; Momsen and Stoerk 2014). These contributions are considered to be of an Explanation theory type as they say what is and provide causal relationships and explanations.

Study 3 also contributes to an Analysis theory type by providing a conceptualization of empirical nudging studies by means of a morphological box with eight dimensions. A morphological box is valuable as it provides an overarching framework for researchers to systematically classify and compare empirical nudging studies. Consequently, it facilitates the identification of contradictory findings as well as potential research gaps. To the best of our knowledge, such an overarching classification mechanism does not exist yet for scientific research studies using the concept of (digital) nudging.

Further, Study 3 contributes to the IS literature, especially to the concept of digital nudging. Firstly, it highlights definition problems of digital nudging. While the definition of Weinmann et al. (2016) only covers user-interface design elements, a digital setting is broader and not limited to mere manipulations of the UI. Secondly, Study 3 empirically compares the effect sizes of nudges in a conventional and a digital setting and concludes that there does not exist any statistical difference in the effect sizes across the two settings. Thirdly, the study provides avenues for future research in the IS community that can be used to develop new or channel existing research projects. These contributions on digital nudging are of an Analysis theory type, too.

Finally, Study 4 contributes to existing research by enhancing the understanding of moderating effects of digital nudges (Explaining and Predicting theory type). It confirms the findings from Study 3 that nudges can have positive as well as negative (i.e. backfire) effects. Thereby, it shows that nudges from offline environments cannot be simply transferred to digital environments. In particular, social norms have to be designed with great care to balance the anchoring effect with the high reference value effect (see Chapter 4.2.5). Further, it claims that the effect of digital nudges does not only depend on the choice architecture, but also on the individual characteristics of the decision-maker, especially on personality traits. This finding is new as researchers have only started to assess moderating effects in digital nudging, and they have not analyzed personality traits in this sense before. Similar to Study 2, the findings are based on testable propositions and predict how individuals with different personality traits respond to different digital nudges.

Overall, this thesis contributes to the research streams of marketing, information systems and behavioral economics which are also depicted at the beginning of Chapter 2.

5.3 Contributions to Practice

An active transfer to practice is an important goal of IS research (Te'eni et al. 2017). Hence, we derive three core contributions for practitioners, especially marketing managers, designers of digital channels as well as policy makers.

Practical contributions for marketing managers

In Study 1, practitioners can use the morphological box as a guideline to evaluate their channels and to analyze whether they match with their consumer base. Firstly, they have to assess which channels they are offering and how these channels are positioned within the firm. Secondly, they should segment their consumers along individual characteristics, such as demographics, psychographics and experience (see dimension "consumer" in the morphological box). This can be done, for instance, by defining target consumers or segments. Thirdly, they can analyze if their channels match the expected consumer segments. If not, marketing managers can actively steer consumer behavior by implementing measures which represent characteristics of the channel attributes. For example, the firm could offer the possibility to order online but to pick-up the order in a certain store, hence extending the breadth of the online product assortment to physical stores. Moreover, other measures could be taken to promote the channel advantages and to reduce the channel disadvantages (e.g. refund money of fraudulent transactions) for certain consumer segments. Finally, practitioners can use the morphological box to review their product portfolio and test it for stage-channel and product-channel associations (Gensler et al. 2012; Verhoef et al. 2007).

Practical contributions for designers of digital channels

In Study 2 and 4, practitioners can use the findings from this work to individualize their digital channels according to the individual user or consumer characteristics. To do so, designers of digital channels can use today's technological advancements of deriving personality traits based on social media data (Bachrach et al. 2012; Markovikj et al. 2013). Then, upon identifying their consumers, they adapt their channels by adding certain channel characteristics (Study 2) or digital nudges (Study 4). For example, the benefits of digital channels, e.g. broad product spectrum or convenience, should be highlighted particularly to introverted consumers or consumers with low neuroticism. In addition, consumers with feminine traits could be reached with risk-reducing messages, privacy and security seals (e.g. Bansal et al. 2015) or other IS artefacts (Lowry et al. 2017). Alternatively, participants with high masculinity have trust in digital channels and they are inclined towards appreciating the benefits of it. This can be exploited in similar ways as for introverted consumers or consumers with low neuroticism, or by adding trust elements to digital channels. To gather the data, providers either ask for the users' permission, or they use publicly available social media data. Although asking for permission might seem unrealistic at first glance, consumers could receive monetary benefits, or be convinced with the promise to close their attitude-behavior gap, in return for their personal data.

Practical contributions for policy makers

Moreover, Study 3 and 4 help policy makers improve policy making in various fields. For example, if policy makers are active in the energy sector, they can draw on the finding that defaults (e.g. Dinner et al. 2011) are much more effective than social norms or disclosures (Allcott 2011; Momsen and Stoerk 2014). However, disclosures are more common in research and easier to implement in cooperation with energy providers. Moreover, several energy providers in Germany are already providing basic systems of energy feedback. With respect to environmentally friendly policies, practitioners can implement the findings, too. We recommend being cautious with the exact wording of social norms when promoting sustainable product choices. Thus, similarly to Halpern (2016), we suggest to pre-test the wording with a small representative sample. These suggestions are in line with the propositions of other researchers (Datta and Mullainathan 2014; Ly et al. 2013).

Finally, we recommend that policy makers can use the spreadsheet with the coded studies as a guiding database when developing new policies. However, we are aware that it is often difficult for practitioners to choose the correct intervention for their purpose. Therefore, we propose a "digital nudging generator" which is based on a recommender system. It could use existing classifications of choice architecture (Johnson et al. 2012; Münscher et al. 2016; Sunstein 2014) and could suggest an appropriate nudge based on a set of criteria (see future research below).

5.4 Limitations

Although all four studies of this thesis were conducted with rigor and relevance (Lee 1999), they have several limitations. Study 1 and Study 3 were primarily coded by only one researcher. Although sections with unclear interpretation were discussed with other knowledgeable researchers, the coding might be biased. This limitation applies more to Study 1 than to Study 3, as the latter mainly extracted effect sizes which are less ambiguous than determinants of multi-channel behavior. Hence, no intercoder reliability could be calculated and other researchers could reach slightly different results.

Moreover, the samples of both empirical studies were dominated by students of the local technical and pedagogical universities. As a consequence, they are not representative for the overall Internet population of Germany (Statista 2018) and the generalizability of the results is limited. This was intended for Study 2 because this study had the aim to replicate and extend the structural model of Kim et al. (2008) which also used a student dominated sample with a similar distribution of age and gender. In Study 4, this limitation is weakened by the fact that students represent the generation which has a high affinity towards online shopping environments, and which is aware of the importance of sustainability (Campbell-Arvai et al. 2014). Moreover, the demographics in Study 4 are akin to previous studies (compare Demarque et al. 2015; Theotokis and Manganari 2015) which employed a similar setting, too.

In addition, Study 3 had the limitation of using the rather strict exclusion criteria of whether the authors of the primary studies labelled their approach a "nudge" or whether they quoted or referred to the original work of Thaler and Sunstein (2008). This ensured the comparability of the selected studies but possibly led to the exclusion of studies that are similar to nudging, and could have been included, too. To account for this potential limitation, we additionally coded and analyzed a randomly selected sample of 20 nudge-like studies. We compared them with the results of Study 3 and could not find major differences in terms of means and variances of the effect sizes (full results not disclosed).

Finally, the monetary payoffs of both empirical studies (Study 2 and Study 4) were not based on performance. Hence, it is debatable whether we measured actual behavior or only intentions. This was done deliberately as a student dominated sample is highly price sensitive and any incentive would have distorted the results. Moreover, the empirical studies did not have the aim to measure rational choices, as it is done in many studies of economics, but rather dependent variables such as channel choice or sustainable product choice. Therefore, we argue that it was not suitable to link the monetary payoff with a hypothetical "optimal" decision.

5.5 Future Research

The four studies provide ample suggestions for future research. While the determinants of multi-channel behavior are well understood by now, other questions remain unsolved. For example, it is still unclear whether the relationship of personality traits, gender roles and channel characteristics can be compensated by decision support systems. A design science research project might be suitable to study to what extent predispositions (e.g. high degree of neuroticism) can be balanced with security features or guidance design features (Arnott 2006; Morana et al. 2017). Thereby, behavioral science and design science can be regarded as complementary paradigms (Wimmer and Yoon 2017).

Moreover, we presumed that an individualized UI increases various outcome variables (such as digital channel choice or usage). However, whether such presumed effects are actually occurring still has to be tested empirically with an adaptive UI. Such testing could assess the individual characteristics and preferences of the consumers in the first place, and then match them in near-time with respective UI design elements, such as risk-reducing messages or privacy and security seals (Bansal et al. 2015; Mousavizadeh et al. 2016).

Study 3 highlights avenues for future research in digital nudging for the IS community. For instance, we present how digital nudges can be combined with NeuroIS or eye-tracking technologies. Hummel, Toreini, et al. (2018) provide an experimental design on this matter that is ready for execution. Moreover, such an experimental setting could also solve the question of Study 4 whether participants with low conscientiousness were focusing more on the warning than participants with high conscientiousness.

In addition, Study 4 and another study not part of this thesis (Hummel et al. 2017b), raise the issue of product dependencies in channel choices. Hence, a follow-up study using digital nudges and personality traits could verify whether nudges interact differently with individual characteristics concerning non-food items (i.e. whether there exists and additional layer of moderation effects).

Further, it would be beneficial to test whether the results of Study 2 and 4 can be replicated with representative samples of the German Internet population, in a real-world setting instead of a laboratory, or with a higher number of participants to ensure the required statistical power and to confirm the identified interaction effects.

Finally, based on the need to match appropriate digital nudges with the requirements of policy makers or designers of digital channels, the IS community could develop a “digital nudging generator”. Using existing classifications for nudging as a starting point (Johnson et al. 2012; Münscher et al. 2016; Sunstein 2014), a decision tree could be developed for defining a guideline for using digital nudges. Based on a set of criteria (e.g. What is the context? What is the dependent variable? Who is the target audience, etc.), it would be possible to develop a recommender system which outputs a suitable digital nudge for practitioners. Ideally, this recommender system would be implemented through a web-based application for the general public as part of a design science research project combining behavioral science and design science (Wimmer and Yoon 2017).

5.6 Concluding Remarks

Current retail channels are going through a major transformation. While traditional channels were complemented with digital channels with the rise of the Internet, most retailers nowadays follow an omni-channel strategy (Bianchi et al. 2016; Cook 2014; Saghiri et al. 2017; Verhoef et al. 2015). These developments, with all their good intentions and outcomes, always have to be balanced with the privacy rights and concerns of users and consumers. Particularly with an ever-increasing amount of data and the associated prevalence of artificial intelligence, the individualization of digital channels can be pushed towards unimaginable accuracy. Especially when nudging consumers, this individualization has to be transparent and in line with legal and ethical standards (von Grafenstein et al. 2018).

Along with the individualization of digital channels, also the accuracy of identifying consumers will increase massively through further technological innovations. In turn, this raises issues of data privacy and fully transparent citizens. It is not surprising that the EU has introduced a new General Data Protection Regulation (GDPR) to address such fears. Moreover, the results were presented to a major German bank which was reluctant to implement an individualization of digital channels based on personality traits. They feared that consumers would close their accounts for reasons of data privacy. Hence, such fears, although mainly left out by this thesis, always have to be balanced against the benefits of an increased individualization of digital channels.

The author of this thesis is well aware that retail channels will continue to evolve and that this thesis leaves many questions unsolved. Therefore, the field of individualized choices and digital nudging in digital channels continues to offer avenues for future research in the disciplines of information systems and marketing.

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Appendix

Appendix A: Zusammenfassung (deutsch)

Motivation

Der Aufstieg neuer Technologien hat in der Vergangenheit kontinuierlich zur Entwicklung und Implementierung neuer digitaler Absatzkanäle (z.B. Online- oder Mobile-Kanal) geführt (Avalaunch Media 2009; Watson et al. 2015). Dies hat ein verändertes Konsumentenverhalten ermöglicht, welches sich durch die Kombination verschiedener Kanäle innerhalb des Kaufprozesses auszeichnet (z.B. Sopadjieva et al., 2017; Verhoef et al., 2007). Sowohl für Konsumenten als auch für Unternehmen hat das veränderte Konsumentenverhalten zahlreiche Auswirkungen. Unternehmen könnten von negativen Konsequenzen betroffen sein, wenn Konsumenten Kanäle mit höheren Transaktionskosten wählen (PwC 2012) oder wenn sie sich in Kanälen eines Unternehmens informieren, aber in Kanälen anderer Unternehmen abschließen (Chiu et al. 2011; Chou et al. 2016). Aber auch Konsumenten profitieren noch nicht vollends von neuen Technologien, beispielsweise indem sich der Kaufprozess verlängern oder es zu konkurrierende Informationen und Erfahrungen zwischen den Kanälen kommen kann (Brynjolfsson et al. 2013; Rawson et al. 2013). Folglich verlassen sich nur wenige Konsumenten ausschließlich auf digitale Kanäle (Sopadjieva et al. 2017).

Das Design von digitalen Kanälen ist ein Lösungsansatz für diese Herausforderungen, da digitale Kanäle eine flexibel gestaltbare Schnittstelle zwischen Konsumenten und Unternehmen bilden. Insbesondere die Individualisierung von digitalen Benutzeroberflächen auf Basis von Persönlichkeitseigenschaften ist in vielerlei Hinsicht effektiver als ein generisches Design für alle (Nov, Arazy, López, et al. 2013) und könnte die Nutzung neuer Technologien erhöhen (Oulasvirta and Blom 2008). Für ein individualisiertes Design ist jedoch Wissen über Interaktionseffekte zwischen den Eigenschaften der digitalen Kanäle und den Nutzereigenschaften notwendig. Innerhalb von digitalen Kanälen ist zudem unklar, wie stark die Effekte einer Individualisierung von digitalen Kanälen auf bestimmte Outcomes, beispielsweise die Wahl von nachhaltigen Produkten, wirken. Designer von digitalen Kanälen können entsprechende Entscheidungen mittels Konzepten aus der Verhaltensökonomie, sogenannten „Nudges“ (Thaler and Sunstein 2008), beeinflussen. Auch hier scheinen individualisierte Nudges einen Mehrwert über standardisierte Nudges zu bieten (Strahilevitz and Porat 2014; Thaler and Sunstein 2008). Allerdings bleibt unklar, auf Basis welcher Eigenschaften eine Individualisierung erfolgen kann.

Alle Studien dieser Doktorarbeit beschäftigen sich daher mit der Analyse und der Individualisierung von Konsumentenverhalten in digitalen Kanälen. Eine grundlegende Analyse von individualisierten (Absatz-)Kanalentscheidungen (Studien 1 und 2) ist dabei Voraussetzung für ein individualisiertes Nudging von Konsumentenentscheidungen (Studien 3 und 4). Dabei werden auch auf Konzepte und

Theorien aus benachbarten Disziplinen zurückgegriffen. Während die ersten beiden Studien auf Konzepte aus dem Marketing und der Psychologie zurückgreifen, basieren Teil 3 und 4 auf Theorien der Verhaltensökonomie, einer Subdisziplin der Volkswirtschaftslehre.

Individualisierte Kanalentscheidungen (Studien 1 und 2)

Die erste Studie[6] widmet sich den Einflussfaktoren von Multikanalverhalten, welches heutiges Konsumentenverhalten auszeichnet (Sopadjieva et al. 2017). Obwohl bereits empirische Studien (z.B. Gensler et al., 2012; Verhoef et al., 2007) und Literaturanalysen (z.B. Trenz and Veit 2015; Zhang and Benyoucef 2016) zum Multikanalverhalten von Konsumenten durchgeführt wurden, ist nicht ganzheitlich geklärt, welche Faktoren zu welcher Kanalnutzung führen und ob alle Studien zu gleichen Ergebnissen kommen. Zudem ist unklar, ob sich die Einflussfaktoren zwischen Produkten und Dienstleistungen unterscheiden. Daher stellen wir folgende Forschungsfrage auf:

> *Was sind Einflussfaktoren auf das Multikanalverhalten für Produkte und Dienstleistungen?*

Die Forschungsfrage wurde mittels einer systematischen Literaturanalyse von 53 wissenschaftlichen Studien beantwortet. Aus diesen Studien wurde eine morphologische Box erstellt, welche Einflussfaktoren und Ergebnisse von Multikanalverhalten in vier Dimensionen gliedert: Kanal, Kontext, Konsument und Produkt. Durch eine numerische Auswertung von Einflussfaktoren für Produkte und Dienstleistungen werden Forschungsschwerpunkte und -lücken herausgearbeitet. Die Studie leistet folglich einen wissenschaftlichen Beitrag, indem sie die Einflussfaktoren von Multikanalverhalten systematisiert und Forschungsfragen für zukünftige Untersuchungen aufzeigt, beispielsweise wie die Kanalwahl von unterschiedlichen Arten von Dienstleistungen moderiert wird.

Basierend auf der systematischen Gliederung der Einflussfaktoren von Multikanalverhalten, widmet sich die zweite Studie[7] der Frage, wie die einzelnen Dimensionen untereinander zusammenhängen und was dies für die Kanalentscheidung bedeutet. Das Wissen über entsprechende Zusammenhänge würde die Möglichkeit zur Individualisierung von Kanälen schaffen. Zwar haben vorherige Studien bereits Persönlichkeitseigenschaften in Online-Kontexten untersucht, dies jedoch nur auf qualitativer Ebene (Florenthal and Shoham 2010; Pieterson and van Dijk 2007) oder mit anderen abhängigen Variablen (Bansal et al. 2010; Bosnjak et al. 2007; Turkyilmaz et al. 2015). Insbesondere ist unklar, ob es Verbindungen zwischen Persönlichkeitseigenschaften, Geschlechterrollen und Kanaleigenschaften gibt, welche beispielsweise für eine Individualisierung des Kanaldesigns genutzt werden könnten. Dies spiegelt sich auch in der folgenden Forschungsfrage wider:

[6] Hummel et al. (2016)
[7] Hummel, Vogel, Schacht et al. (2018)

Was ist der Einfluss von Persönlichkeitseigenschaften und Geschlechterrollen auf das wahrgenommene Risiko, Vertrauen und den wahrgenommenen Nutzen von Online-Kanälen?

Zur Beantwortung der Forschungsfrage haben wir auf einem existierenden Modell (Kim et al. 2008) aufgebaut und im Sommer 2017 ein Laborexperiment mit 236 Teilnehmern durchgeführt. Die gewonnenen Daten wurden mittels eines Strukturgleichungsmodells analysiert (kovarianzbasierter Ansatz). Dabei fanden wir einen Zusammenhang zwischen Persönlichkeitseigenschaften, Geschlechterrollen und Kanaleigenschaften. Beispielsweise korreliert die Eigenschaft Verträglichkeit positiv mit Vertrauen und die Eigenschaft Neurotizismus stark negativ mit dem wahrgenommenen Nutzen des Online-Kanals. Die Ergebnisse sind eine theoretische Erweiterung des ursprünglichen Grundmodells (Kim et al. 2008) um Persönlichkeitseigenschaften und Geschlechterrollen. Designer von digitalen Kanälen können die Erkenntnisse nutzen, um die Kanäle auf die individuellen Eigenschaften der Konsumenten zu individualisieren, z.B. indem Daten über Persönlichkeitseigenschaften aus sozialen Medien abgeleitet werden (Bachrach et al. 2012; Markovikj et al. 2013).

Mit dem Verständnis, wie individuelle Charakteristika mit Kanaleigenschaften zusammenhängen, können nun Konsumentenentscheidungen in digitalen Kanälen beeinflusst werden. Dies kann insbesondere mit Konzepten der Verhaltensökonomie, sogenannten „Nudges“ (Thaler and Sunstein 2008), erreicht werden. Damit wird auch auf einen Forschungsaufruf reagiert, Konzepte der Verhaltensökonomie in die Disziplin der Wirtschaftsinformatik einzubeziehen (Goes 2013).

Nudging von Konsumentenentscheidungen in digitalen Kanälen (Studie 3 und 4)

Die dritte Studie[8] greift das Konzept Nudging (Thaler and Sunstein 2008) auf, welches bereits von zahlreichen Regierungen für Gesetzesentwürfe angewendet wird (Behavioral Insights Team 2016; Social and Behavioral Sciences Team 2016). Allerdings lassen mehrere Studien (z.B. Sunstein, 2017) Zweifel aufkommen, ob Nudging uneingeschränkt wirksam ist. Insbesondere ist unklar, wie gut, und unter welchen Umständen, Nudging funktioniert. Bisherige Literaturanalysen zu dem Thema fokussieren sich entweder nur auf einen Bereich, wie beispielsweise Gesundheit (Adam and Jensen 2016; Wilson et al. 2016), erheben keine Effektstärken (Mirsch et al. 2017) oder umfassen nur wenige Studien (Benartzi et al. 2017; Skov et al. 2013). Daher untersuchen wir folgende Forschungsfrage:

Wie können Nudges klassifiziert werden und was sind die Einflussfaktoren für die Effektstärke von unterschiedlichen Kategorien von Nudges?

[8] Hummel and Maedche (2018)

Um die Forschungsfragen zu beantworten haben wir eine quantitative Literaturanalyse durchgeführt. Basierend auf 100 empirischen Studien haben wir zunächst eine morphologische Box entwickelt, die bisherige Nudging-Studien anhand von acht Dimension klassifiziert. Aufbauend darauf wird eine quantitative Analyse zu den Effektstärken der Studien durchgeführt. Unsere Analyse zeigt beispielsweise, dass nur rund 2/3 der Effekte signifikant sind und stark nach Art des Nudges variieren. Zudem formulieren wir sechs zentrale Bereiche für zukünftige Forschungsvorhaben. Zusammenfassend erweitert diese Studie das theoretische Wissen zu Nudging und bietet praktische Implikationen, beispielsweise indem Entscheidungsträger bei Gesetzgebungsverfahren auf empirisches Wissen zurückgreifen können.

Die vierte und letzte Studie[9] greift die Ergebnisse von Studie 3 auf und beschäftigt sich mit dem akuten Problem von mangelndem nachhaltigen Konsumentenverhalten, insbesondere im Bereich von Kaufentscheidungen nachhaltiger Produkte. Obwohl viele Konsumenten angeben, mehr nachhaltige Produkte kaufen zu wollen, tun dies nur rund 20% (Kristensson et al. 2017). Dieses Phänomen wird auch als „Attitude-Behavior-Gap" bezeichnet (Ajzen 1991; Vermeir and Verbeke 2006). Digitale Nudges (Weinmann et al. 2018) können helfen, diese Lücke zu schließen und die Wahl nachhaltiger Produkte zu erhöhen. Basierend auf der quantitativen Literaturanalyse (Studie 3) sind besonders die Nudges der Vorauswahl, sozialen Normen und Warnungen von hohen Effektstärken gekennzeichnet. Darüber hinaus, und aufbauend auf Studie 2, beschäftigt sich die letzte Studie damit, ob die Effektivität von Digitalen Nudges von Persönlichkeitseigenschaften moderiert wird. Daher wird folgende Forschungsfrage untersucht:

> *Wie beeinflussen unterschiedliche Arten von digitalen Nudges (Vorauswahl, soziale Normen und Warnungen) die Wahl von nachhaltigen Produkten in Online-Kanälen unter Berücksichtigung von Persönlichkeitseigenschaften?*

Zur Beantwortung dieser Forschungsfrage wurde im Sommer 2018 ein onlinebasiertes Fragebogenexperiment mit 452 Teilnehmern durchgeführt. Die Ergebnisse zeigen, dass die Vorauswahl von nachhaltigen Produkten deren Kaufwahrscheinlichkeit signifikant steigert, während soziale Normen zu einer Reduktion der Kaufwahrscheinlichkeit führen. Diese Effekte werden teilweise von Persönlichkeitseigenschaften moderiert, sodass beispielsweise eine Vorauswahl besser auf Teilnehmer wirkte, welche ein hohes Maß an Offenheit für neue Erfahrungen aufweisen. Die Studie trägt damit zu einer Weiterentwicklung des Digitalen Nudgings bei und wirft ein neues Licht auf das Zusammenspiel zwischen Digitalen Nudges und Persönlichkeitseigenschaften, welche die erwarteten Effekte verstärken oder abschwächen können.

[9] Hummel, Vogel and Maedche (2018)

Theoretisch leistet diese Dissertation einen Beitrag zum Stand der Forschung in der Wirtschaftsinformatik und im Marketing. Erstens wird das theoretische Modell von Kim et al. (2008) erweitert und gezeigt, wie Persönlichkeitseigenschaften mit Kanaleigenschaften zusammenhängen. Insbesondere reicht es im digitalen Zeitalter nicht aus, die digitalen Kanäle isoliert zu entwerfen, sondern es müssen stets die Interaktionseffekte mit den individuellen Eigenschaften der Konsumenten berücksichtigt werden. Zweitens verbessert die Arbeit das Verständnis von Multikanalverhalten und zeigt auf, welche relevanten Faktoren zu welchem Kanalverhalten führen. Dabei werden auch Forschungslücken von Multikanalverhalten im Kontext von Dienstleistungen aufgedeckt. Drittens konzeptualisiert die Arbeit verschiedene Studien aus dem Bereich Nudging mittels einer morphologischen Box. Dabei werden die Stärken und Grenzen von Nudging aufgezeigt und mittels einer quantitativen Analyse die mittleren Effektstärken verschiedener Arten von Nudges beleuchtet. Darüber hinaus formulieren wir sechs zentrale Bereiche für zukünftige Forschungsvorhaben. Viertens trägt diese Arbeit zu einem verbesserten Verständnis der Wirkungsweise von digitalen Nudges bei, welche im Bereich von nachhaltigen Produktentscheidungen von Persönlichkeitseigenschaften moderiert werden. Zuletzt wird gezeigt, dass Nudges sowohl positive als auch negative Effekte haben können, und dass das Design von sozialen Normen behutsam erfolgen muss.

Praktische Anwendungen bestehen für Designer von digitalen Kanälen. So können diese die Zusammenhänge von Persönlichkeits- und Kanaleigenschaften (Studie 2) sowie von Digitalen Nudges und Persönlichkeitseigenschaften (Studie 4) für ein individualisiertes Design von digitalen Kanälen verwenden. In Zeiten, in denen Persönlichkeitseigenschaften von Daten aus sozialen Medien abgeleitet werden können (Bachrach et al. 2012; Markovikj et al. 2013), kann das Design von digitalen Kanälen adaptiv verändert werden. Denkbar wäre auch, Konsumenten die Option zu geben, diese Daten im Austausch für bessere Angebote oder einer Schließung des „Attitude-Behavior-Gap" selbst zur Verfügung stellen zu lassen. Zudem können Gesetzgeber und Entscheidungsträger im Umweltbereich die Ergebnisse von Studie 4 nutzen, um den Verkauf nachhaltiger Produkte zu stimulieren. Dabei sind Vorauswahl von Produkten im digitalen Kontext, soweit gesetzlich zulässig, effektiver als soziale Normen.

Appendix B: Measurement items for Study 2 and Study 4

Table 24. Measurement items (Study 2)

Construct	Measurement items (German)	Measurement items (English)	Source
Perceived risk	Wie würden Sie insgesamt Ihre Risikowahrnehmung dieser Webseite beurteilen?	How would you rate your overall perception of risk from this site?	Kim et al. (2008)
	Von dieser Webseite zu kaufen, würde mehr Produktrisiken (z.B. falsches Produkt) mit sich bringen verglichen mit traditionelleren Einkaufsmöglichkeiten.	Purchasing from this Website would involve more product risk (i.e. not working, defective product) when compared with more traditional ways of shopping.	
	Von dieser Webseite zu kaufen, würde mehr finanzielle Risiken (z.B. Betrug, schwierig zurückzugeben) mit sich bringen verglichen mit traditionelleren Einkaufsmöglichkeiten.	Purchasing from this Website would involve more financial risk (i.e. fraud, hard to return) when compared with more traditional ways of shopping.	
Perceived benefits	Wenn ich die Webseite einer Bank nutze, kann ich Zeit sparen.	I can save time by using this Website.	Kim et al. (2008)
	Ich finde es bequem, die Webseite einer Bank zu nutzen.	I think using this Website is convenient.	
	Durch das Nutzen von Webseiten von Banken kann ich die Aufgabe viel schneller durchführen, als über die Filiale.	Using this Website enables me to accomplish a shopping task more quickly than using traditional stores.	
Internet trust	Bewerten Sie das Ausmaß, mit welchem Sie den folgenden Aussagen zustimmen: Internet-Webseiten sind sichere Umgebungen, um Informationen mit anderen auszutauschen	Rate the extent to which you agree with the following statements: Internet websites are safe environments in which to exchange information with others.	Dinev and Hart (2006)
	… Internet-Webseiten sind zuverlässige Umgebungen, um geschäftliche Transaktionen durchzuführen.	… Internet websites are reliable environments in which to conduct business transactions.	
	… Internet-Webseiten behandeln persönliche Informationen, die von Nutzern übermittelt wurden, in einer kompetenten Weise.	… Internet websites handle personal information submitted by users in a competent fashion.	
Extraversion	... gesprächig ist, sich gerne unterhält.	Is talkative	

	... eher zurückhaltend und reserviert ist.	Is reserved	John and Srivastava (1999); Lang et al. (2001)
	... voller Energie und Tatendrang ist.	Is full of energy	
	... begeisterungsfähig ist, andere mitreißen kann.	Generates a lot of enthusiasm	
	... eher still und wortkarg ist.	Tends to be quiet	
	... durchsetzungsfähig und energisch ist.	Has an assertive personality	
	... manchmal schüchtern und gehemmt ist.	Is sometimes shy, inhibited	
	... aus sich herausgeht, gesellig ist.	Is outgoing, sociable	
Agreeableness	... dazu neigt, andere zu kritisieren.	Tends to find fault with others	John and Srivastava (1999); Lang et al. (2001)
	... hilfsbereit und selbstlos gegenüber anderen ist.	Is helpful and unselfish with others	
	... häufig in Streitereien verwickelt ist.	Starts quarrels with others	
	... nicht nachtragend ist, anderen leicht vergibt.	Has a forgiving nature	
	... anderen Vertrauen schenkt.	Is generally trusting	
	... sich kalt und distanziert verhalten kann.	Can be cold and aloof	
	... rücksichtsvoll und einfühlsam zu anderen ist.	Is considerate and kind to almost everyone	
	... schroff und abweisend zu anderen sein kann.	Is sometimes rude to others	
Conscientious-ness	... Aufgaben gründlich erledigt.	Does a thorough job	John and Srivastava (1999); Lang et al. (2001)
	... etwas achtlos sein kann.	Can be somewhat careless	
	... zuverlässig ist und gewissenhaft.	Is a reliable worker	
	... dazu neigt, unordentlich zu sein.	Tends to be disorganized	
	... bequem ist und zur Faulheit neigt.	Tends to be lazy	
	... nicht aufgibt, ehe die Aufgabe erledigt ist.	Perseveres until the task is finished	
	... tüchtig ist und flott arbeitet.	Does things efficiently	
	... Pläne macht und diese auch durchführt.	Makes plans and follows through with them	
	... leicht ablenkbar ist, nicht bei der Sache bleibt.	Is easily distracted	
Neuroticism	... deprimiert, niedergeschlagen ist.	Is depressed, blue	

	... entspannt ist, sich durch Stress nicht aus der Ruhe bringen lässt.	Is relaxed, handles stress well	John and Srivastava (1999); Lang et al. (2001)
	... leicht angespannt reagiert.	Can be tense	
	... sich viele Sorgen macht.	Worries a lot	
	... nicht leicht aus der Fassung zu bringen ist.	Is emotionally stable, not easily upset	
	... ruhig bleibt, selbst in angespannten Situationen ausgeglichen ist.	Remains calm in tense situations	
	... leicht nervös und unsicher wird.	Gets nervous easily	
Openness	... originell ist, neue Ideen entwickelt.	Is original, comes up with new ideas	John and Srivastava (1999); Lang et al. (2001)
	... vielseitig interessiert ist.	Is curious about many different things	
	...tiefsinnig ist, gern über Sachen nachdenkt.	Is ingenious, a deep thinker	
	... eine lebhafte Vorstellungskraft hat, fantasievoll ist.	Has an active imagination	
	... erfinderisch und einfallsreich ist.	Is inventive	
	... künstlerische und ästhetische Eindrücke schätzt.	Values artistic, aesthetic experiences	
	... routinemäßige und einfache Aufgaben bevorzugt.	Prefers work that is routine	
	... gerne Überlegungen anstellt, mit Ideen spielt.	Likes to reflect, play with ideas	
	... nur wenig künstlerisches Interesse hat.	Has few artistic interests	
	... sich gut in Musik, Kunst und Literatur auskennt.	Is sophisticated in art, music, or literature	
Masculinity	Verteidige eigene Meinung	Defend my own beliefs	Hunt et al. (2007); Sieverding (2009)
	Unabhängig	Independent	
	Durchsetzungsfähig	Assertive	
	Starke Persönlichkeit	Strong personality	
	Kraftvoll	Forceful	
	Habe Führungsqualitäten	Have leadership abilities	
	Bereit, etwas zu riskieren	Willing to take risks	
	Dominant	dominant	
	Bereit, Stellung zu beziehen	Willing to take a stand	

	Angriffslustig	Aggressive	
Femininity	Herzlich	Affectionate	Hunt et al. (2007); Sieverding (2009)
	Mitfühlend	Sympathetic	
	Sensibel für die Bedürfnisse anderer	Sensitive to the needs of others	
	Verständnisvoll	Understanding	
	Anteilnehmend	Compassionate	
	Bemüht, verletzte Gefühle zu besänftigen	Eager to soothe hurt feelings	
	Warmherzig	Warm	
	Zart	Tender	
	Liebe Kinder	Loves children	
	Sanft	Gentle	

Table 25. Measurement items (Study 4)

Construct	**Measurement items (German)**	**Measurement items (English)**	**Source**
Extraversion	See above	See above	See above
Agreeableness	See above	See above	See above
Conscientious.	See above	See above	See above
Neuroticism	See above	See above	See above
Openness	See above	See above	See above
Intention	Wenn es Bio-Lebensmittel in Supermärkten gibt, würde ich sie kaufen.	If organic foods were available in the shops, I would buy them.	Teng and Wang (2015)
	Ich bin bereit, trotz höherer Preise Bio-Lebensmittel zu kaufen.	I am willing to buy organic foods despite their higher prices.	
	Die Wahrscheinlichkeit, dass ich Bio-Lebensmittel kaufen würde, ist sehr hoch.	the probability I would buy organic foods is very high.	

Attitude	Bio-Lebensmittel haben geringere chemische Rückstände als herkömmliche Lebensmittel.	Organic foods have lower chemical residues than conventional foods.	
	Bio-Lebensmittel sind sicherer zu essen als herkömmliche Lebensmittel.	Organic foods are safer to eat than conventional foods.	
	Bio-Lebensmittel sind gesünder zu essen als herkömmliche Lebensmittel.	Organic foods are healthier to eat than conventional foods.	
	Bio-Lebensmittel haben eine bessere Qualität als konventionelle Lebensmittel.	Organic foods have superior quality than conventional food.	
Trust	Ich denke, dass sich Unternehmen im Bereich der Bio-Lebensmittel ihrer Verantwortung bewusst sind.	I think that corporations in the field of organic foods are aware of their responsibilities.	
	Ich vertraue darauf, dass diejenigen, die zertifizierte Bio-Lebensmittel verkaufen, auch tatsächlich hochwertige Bio-Lebensmittel verkaufen.	I trust those who sell certified organic foods indeed sell quality organic foods.	
	Ich vertraue auf ein hochwertiges Bio-Label oder -Logo.	I trust a quality organic food label or logo.	
	Ich vertraue den Institutionen, die Bio-Lebensmittel zertifizieren.	I trust the institutions certifying organic food products.	
Norm	Meine Familie denkt, ich sollte Bio-Lebensmittel kaufen.	My family think I should buy organic foods.	
	Meine Freunde denken, ich sollte Bio-Lebensmittel kaufen.	My friends think I should buy organic foods.	
	Nachrichten und Zeitschriften beeinflussen meine Kaufentscheidungen für Bio-Lebensmittel.	News and magazines affect my purchase decisions of organic foods.	
	Staatliche Unterstützung für Bio-Lebensmittel beeinflusst meine Kaufentscheidung für Bio-Lebensmittel.	Government supports for organic foods affect my decisions to buy organic foods.	
Environmental knowledge	Ich weiss, dass ich Produkte und Verpackungen kaufe, die umweltfreundlich sind.	I know that I buy products and packages that are environmentally safe.	Mostafa (2007)
	Ich weiss mehr über Recycling als eine durschnittliche Person.	I know more about recycling than the average person.	
	Ich weiß, wie man Produkte und Verpackungen auswählt, die das Abfallaufkommen auf Deponien reduzieren.	I know how to select products and packages that reduce the amount of waste ending up in landfills.	

	Ich verstehe die Umwelt-Formulierungen und -Symbole auf Produktverpackungen.	I understand the environmental phrases and symbols on product package.	
	Ich kenne mich mit Umweltfragen sehr gut aus.	I am very knowledgeable about environmental issues.	
Nudge rating	Die Bundesregierung fordert ein "Ampelsystem" für Lebensmittel, bei dem gesunde Lebensmittel mit einem kleinen grünen Etikett, ungesunde Lebensmittel mit einem kleinen roten Etikett und Lebensmittel, die weder besonders gesund noch besonders ungesund sind, mit einem kleinen gelben Etikett verkauft werden.	The federal government requires a “traffic lights” system for food, by which healthy foods would be sold with a small green label, unhealthy foods with a small red label, and foods that are neither especially healthy nor especially unhealthy with a small yellow label.	Reisch and Sunstein (2016)
	Ein Gesetz verlangt von allen großen Lebensmittelgeschäften, dass sie ihre gesündesten Lebensmittel an einer prominenten, sichtbaren Stelle platzieren.	A state law requires all large grocery stores to place their most healthy foods in a prominent, visible location.	
	Um Fettleibigkeit bei Kindern zu reduzieren, führt die Regierung eine öffentliche Aufklärungskampagne durch, die aus Informationen besteht, die Eltern nutzen können, um gesündere Entscheidungen für ihre Kinder zu treffen.	To reduce childhood obesity, the national government adopts a public education campaign, consisting of information that parents can use to make healthier choices for their children.	
	Die Bundesregierung verlangt von den Fluggesellschaften, dass sie mit ihren Flugtickets einen bestimmten Betrag zum Ausgleich ihrer CO2-Emissionen berechnen (ca. 10 EUR pro Ticket); im Rahmen des Programms kann man sich aus der Zahlung zurückziehen, wenn man ausdrücklich erklärt, dass man sie nicht bezahlen will.	The federal government requires airlines to charge people, with their airline tickets, a specific amount to offset their carbon emissions (about 10 EUR per ticket); under the program, people can opt out of the payment if they explicitly say that they do not want to pay it.	
	Aus Gründen der öffentlichen Gesundheit und des Klimaschutzes verlangt die Bundesregierung, dass Kantinen in öffentlichen Einrichtungen (Schulen, öffentliche Verwaltungen u.ä.) einen fleischfreien Tag pro Woche haben.	For reasons of public health and climate protection, the federal government requires canteens in public institutions (schools, public administrations and similar) to have one meat-free day per week.	

Appendix C: Additional material for Study 2 and Study 4

Study 2: The Role of Personality Traits and Gender Roles to Individualize Digital Retail Channels

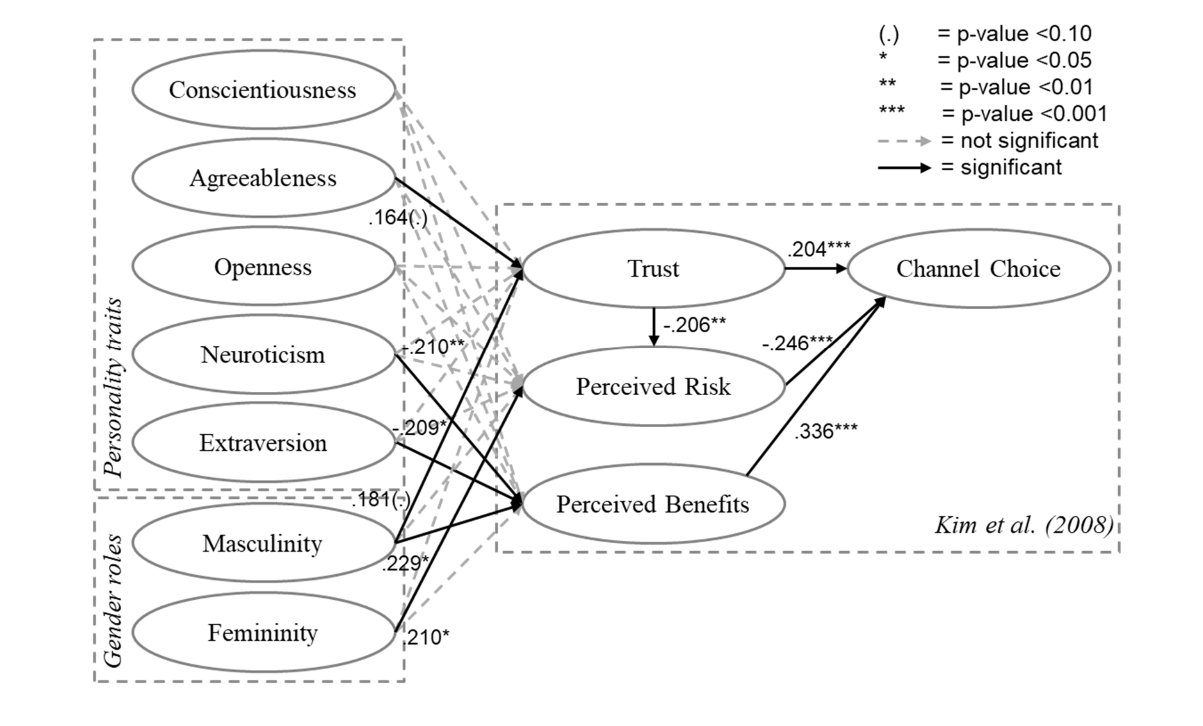

Figure 22. Full research model (Study 2)

Study 4: Individualized Digital Nudges for Sustainable Product Choices in Digital Retail Channels

Table 26. Regression output of mixed effects logistic regression model of main treatment effects

Treatment	Estimate	Std. error	T value	P-value
Intercept	1.0255	0.2758	3.718	**p<0.001*** **
Default	1.5151	0.3641	4.162	**p<0.001*** **
Social	-0.6814	0.3653	-1.865	**0.0621(.)**
Warnings	0.1516	0.3311	0.458	0.6470
Product category bread	-1.0710	0.1885	-5.682	**p<0.001*** **
Product category coffee	-0.4344	0.1871	-2.322	**0.0202***
Product category milk	0.1986	0.1901	1.044	0.2963
Product category pasta	-1.9020	0.1974	-9.636	**p<0.001*** **
Product category tomatoes	0.7573	0.1968	3.847	**p<0.001*** **
AIC / BIC	2,799.6 / 2,858.6			
Observations / ids	2,712 / 452			
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '(.)' 0.1; bananas serve as the reference category				

Table 27. Regression output of mixed effects logistic regression model including personality traits					
Treatment	**Category**	**Estimate**	**Std. error**	**T value**	**P-value**
Intercept	Intercept	0.9740	0.2758	3.532	**p<0.001*** **
Default	Treatment	1.4389	0.3646	3.947	**p<0.001*** **
Social norms		-0.6378	0.3646	-1.749	**0.080(.)**
Warnings		0.2400	0.3328	0.721	0.471
Extraversion	Personality	-0.0391	0.2724	-0.144	0.886
Openness		-0.2530	0.2763	-0.916	0.360
Agreeableness		0.3491	0.2489	1.403	0.162
Conscientiousness		0.3295	0.2402	1.372	0.171
Neuroticism		0.1993	0.2484	0.802	0.422
Default x Extraversion	Interaction	-0.4965	0.4195	-1.184	0.237
Social norms x Extraversion		0.0472	0.3918	0.120	0.904
Warnings x Extraversion		0.1503	0.3712	0.405	0.686
Default x Openness		0.7579	0.4164	1.820	**0.069(.)**
Social norms x Openness		0.2111	0.3932	0.537	0.591
Warnings x Openness		0.3552	0.3632	0.978	0.328
Default x Agreeableness		-0.0740	0.3878	-0.191	0.849
Social norms x Agreeableness		-0.2752	0.3712	-0.741	0.458
Warnings x Agreeableness		0.0290	0.3484	0.083	0.934
Default x Conscientiousness		0.1666	0.3895	0.428	0.669
Social norms x Conscientiousness		-0.4073	0.3751	-1.086	0.278
Warnings x Conscientiousness		-0.5900	0.3454	-1.708	**0.088(.)**
Default x Neuroticism		-0.2140	0.3861	-0.554	0.579
Social x Neuroticism		-0.2929	0.3702	-0.791	0.429
Warnings x Neuroticism		-0.1635	0.3562	-0.459	0.646
Product category bread	Product categories	-1.0723	0.18861	-5.685	**p<0.001*** **
Product category coffee		-0.4350	0.18722	-2.323	**0.020***
Product category milk		0.1989	0.19029	1.045	0.296
Product category pasta		-1.9035	0.19747	-9.639	**p<0.001*** **
Product category tomatoes		0.7585	0.19701	3.850	**p<0.001*** **
AIC / BIC	2,821.9 / 2,999.0				
Observations / ids	2,712 / 452				
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '(.)' 0.1; product category bananas serves as the reference category for the other product categories					

Appendix D: List of primary studies for systematic literature reviews

Study 1: Determinants of Multi-Channel Behavior: Exploring Avenues for Future Research in the Services Industry

Albesa 2007; Ansari et al. 2008; Balasubramanian et al. 2005; Bellman et al. 1999; Bickle et al. 2006; Black et al. 2002; Burke 2002; Chiu et al. 2011; Choi and Park 2006; Chou et al. 2016; Cortinas et al. 2010; Dholakia et al. 2005, 2010; Farag et al. 2006; Florenthal and Shoham 2010; Frambach et al. 2008; Frasquet et al. 2015; Gensler et al. 2007, 2012; Gupta et al. 2004; Heitz-Spahn 2013; Hsiao et al. 2012; Inman et al. 2004; Keen et al. 2004; De Keyser et al. 2015; Konus et al. 2008; Konuş et al. 2014; Kumar and Venkatesan 2005; Lamberti et al. 2014; Laukkanen 2007; Levin et al. 2003; Maity and Dass 2014; Mathwick et al. 2001; McGoldrick and Collins 2007; Melis et al. 2015; Michaelidou et al. 2005; Montoya-Weiss et al. 2003; Nicholson et al. 2002; Noble et al. 2005; Pantano and Viassone 2015; Pookulangara et al. 2011; Schoenbachler and Gordon 2002; Schröder and Zaharia 2008; Sonderegger-Wakolbinger and Stummer 2015; Soopramanien and Robertson 2007; Sorce et al. 2005; Strebel et al. 2004; Sullivan and Thomas 2004; Thomas and Sullivan 2005; Tse and Yim 2001; Venkatesan et al. 2007; Verhoef et al. 2007; Wolfinbarger and Gilly 2001

The spreadsheet with the coding of the primary studies can be obtained from the authors upon request.

Study 3: How Effective Is Nudging? A Quantitative Literature Review on the Effect Sizes and Limits of Empirical Nudging Studies

Agarwal et al. 2017; Aldrovandi et al. 2015; Allcott 2011; Almuhimedi et al. 2015; Altmann and Traxler 2014; Apesteguia et al. 2013; Baek et al. 2014; Bartke et al. 2017; Bettinger and Baker 2011; Bronchetti et al. 2013; Brune et al. 2017; Bull 2012; Calzolari and Nardotto 2016; Campbell-Arvai et al. 2014; Castleman and Page 2015; Chang et al. 2016; Chapman et al. 2010; Cioffi et al. 2015; Cohen et al. 2017, 2015; Costa and Kahn 2011; Cravener et al. 2015; Cyan et al. 2017; Czap et al. 2012, 2015; D'Adda et al. 2017; Damgaard and Gravert 2016; Dayan and Bar-Hillel 2011; Demarque et al. 2015; Dinner et al. 2011; Dogruel et al. 2017; Egebark and Ekström 2016; Ensaff et al. 2015; Esposito et al. 2017; Fellner et al. 2013; Fonseca and Grimshaw 2017; Friis et al. 2017; Gallus 2016; Goswami and Urminsky 2016; Graham et al. 2017; Guerassimoff and Thomas 2015; Hanks et al. 2012; Hedlin and Sunstein 2016; Hermstrüwer and Dickert 2017; Hershfield et al. 2011; Hilton et al. 2014; Holt et al. 2010; Huang et al. 2017; Kallbekken and Sælen 2013; Kattelmann et al. 2014; Keller et al. 2015; Khern-am-nuai et al. 2017; Kongsbak et al. 2016; Kristensson et al. 2017; Kroese et al. 2015; Kuhfuss et al. 2016; Kwok et al. 2016; Lee et al. 2017; Lehmann et al. 2016; Libotte et al. 2014; Loeb et al. 2017; Löfgren et al. 2012; Luoto et al. 2014; Malone and Lusk 2017; Matthies et al. 2016; Miesler et al. 2017; Milkman et al. 2011;

Miller et al. 2016; Missbach and König 2016; Momsen and Stoerk 2014; Newell and Siikamäki 2013; Nickerson and Rogers 2010; Ölander and Thøgersen 2014; Olstad et al. 2014; Östervall 2017; Puaschunder 2017; Rivers et al. 2017; Rodríguez-Priego et al. 2016; Rommel et al. 2015; Rosenkranz et al. 2017; Rozin et al. 2011; Schneider and Graham 2017; Schneider et al. 2017; Seward et al. 2016; Sonntag and Zizzo 2015; Stämpfli et al. 2017; Stämpfli and Brunner 2016; Steffel et al. 2016; Stutzer et al. 2011; Sudarshan 2017; Székely et al. 2016; Tasoff and Letzler 2014; Theotokis and Manganari 2015; Thorndike et al. 2012, 2014; Tietz et al. 2016; Tijssen et al. 2017; Wansink and Hanks 2013; Wong et al. 2015; Zarghamee et al. 2017

The spreadsheet with the coding of the primary studies can be obtained from the authors upon request.

Appendix E: Screenshots of experiment prototypes

Study 2: The Role of Personality Traits and Gender Roles to Individualize Digital Retail Channels

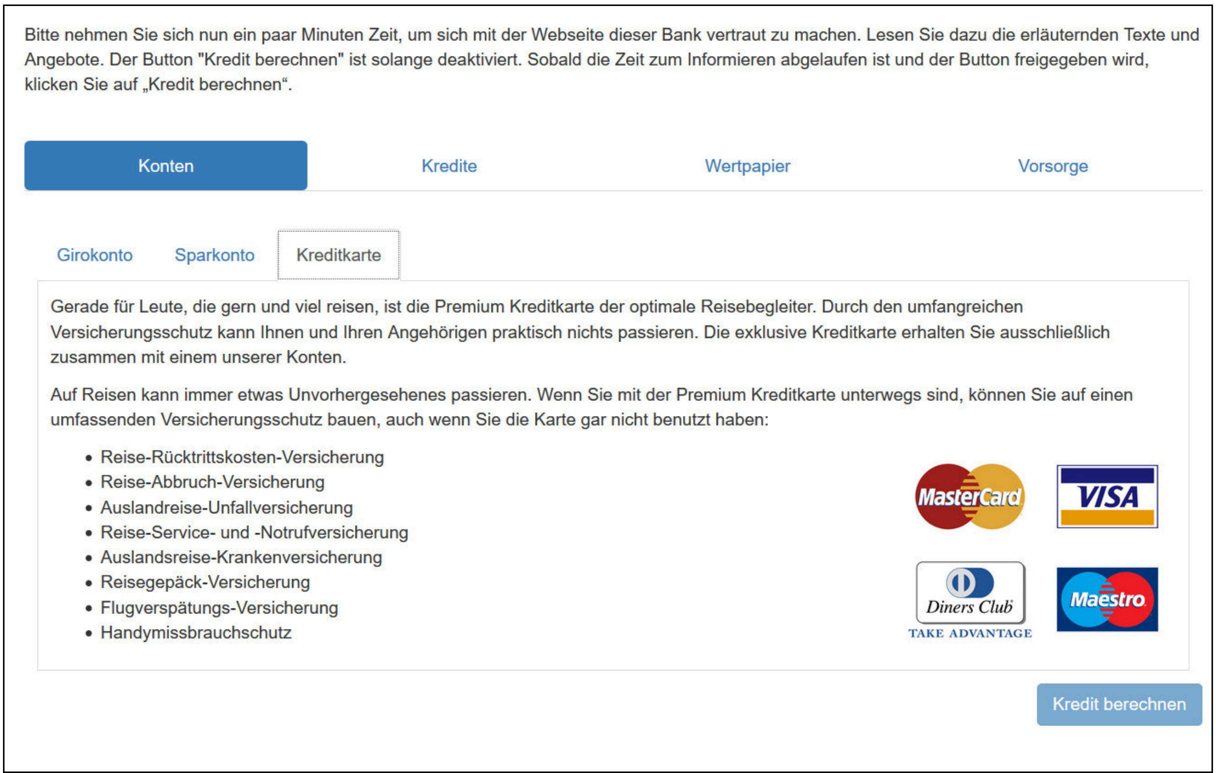

Figure 23. Screenshot of banking website for information stage (Study 2)

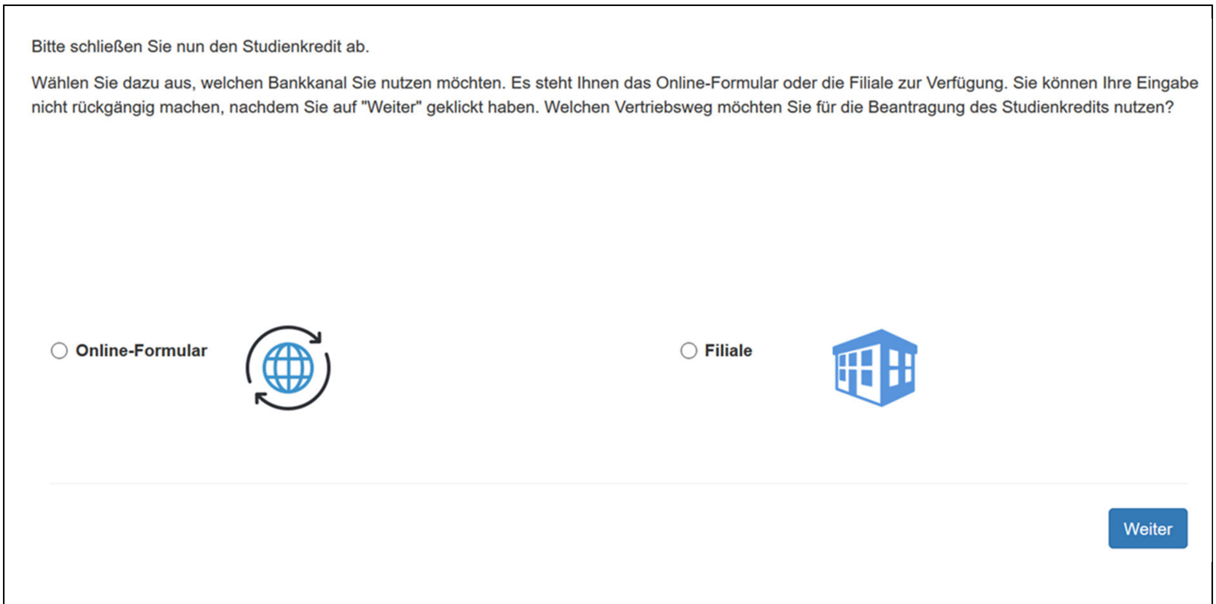

Figure 24. Screenshot of banking website for channel choice (Study 2)

Study 4: Individualized Digital Nudges for Sustainable Product Choices in Digital Retail Channels

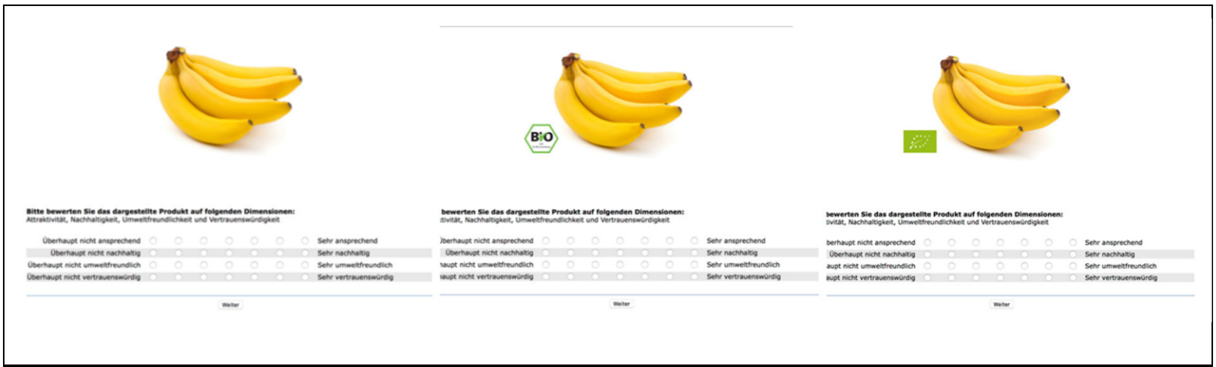

Figure 25. Exemplary screenshot of the different labels of the pre-test (Study 4)

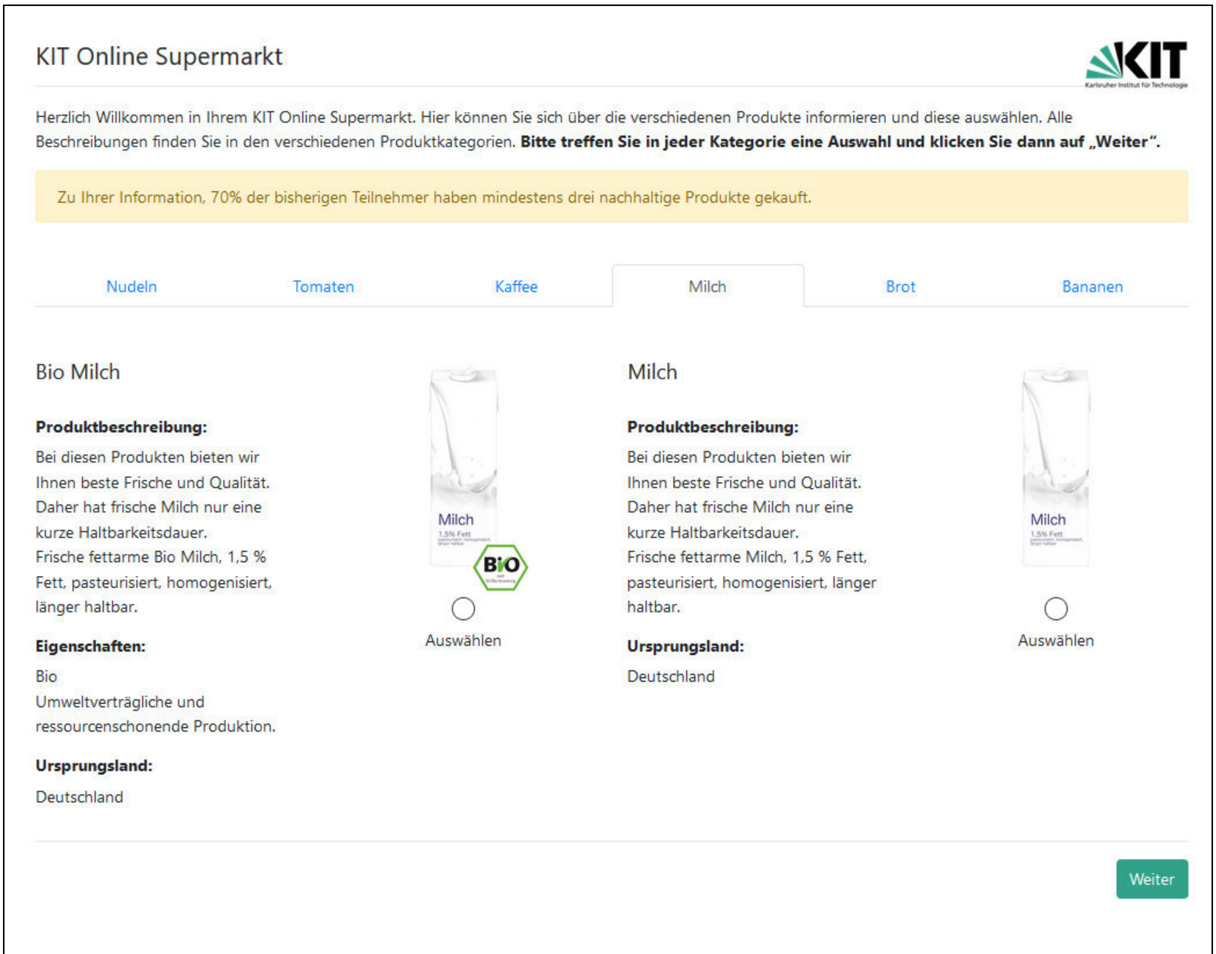

Figure 26. Screenshot of online shop with social norms nudge (Study 4)

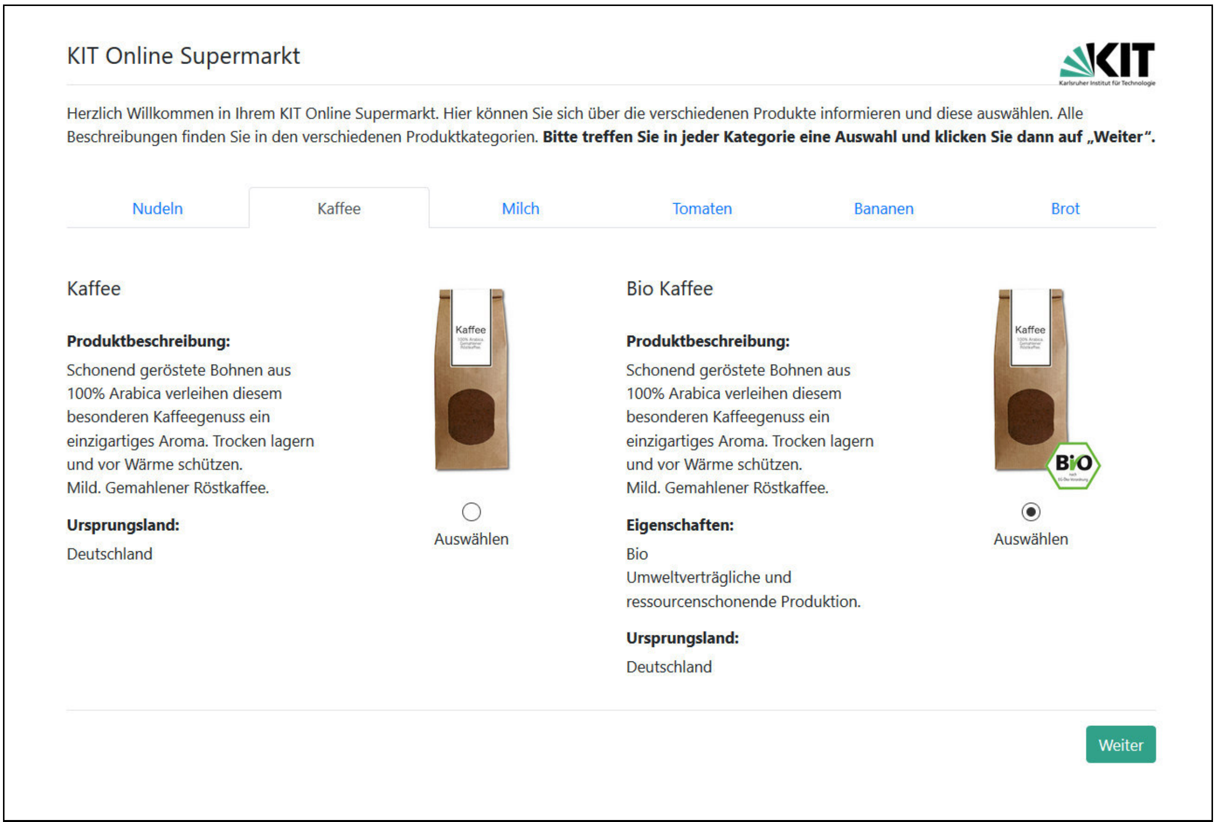

Figure 27. Screenshot of online shop with default nudge (Study 4)

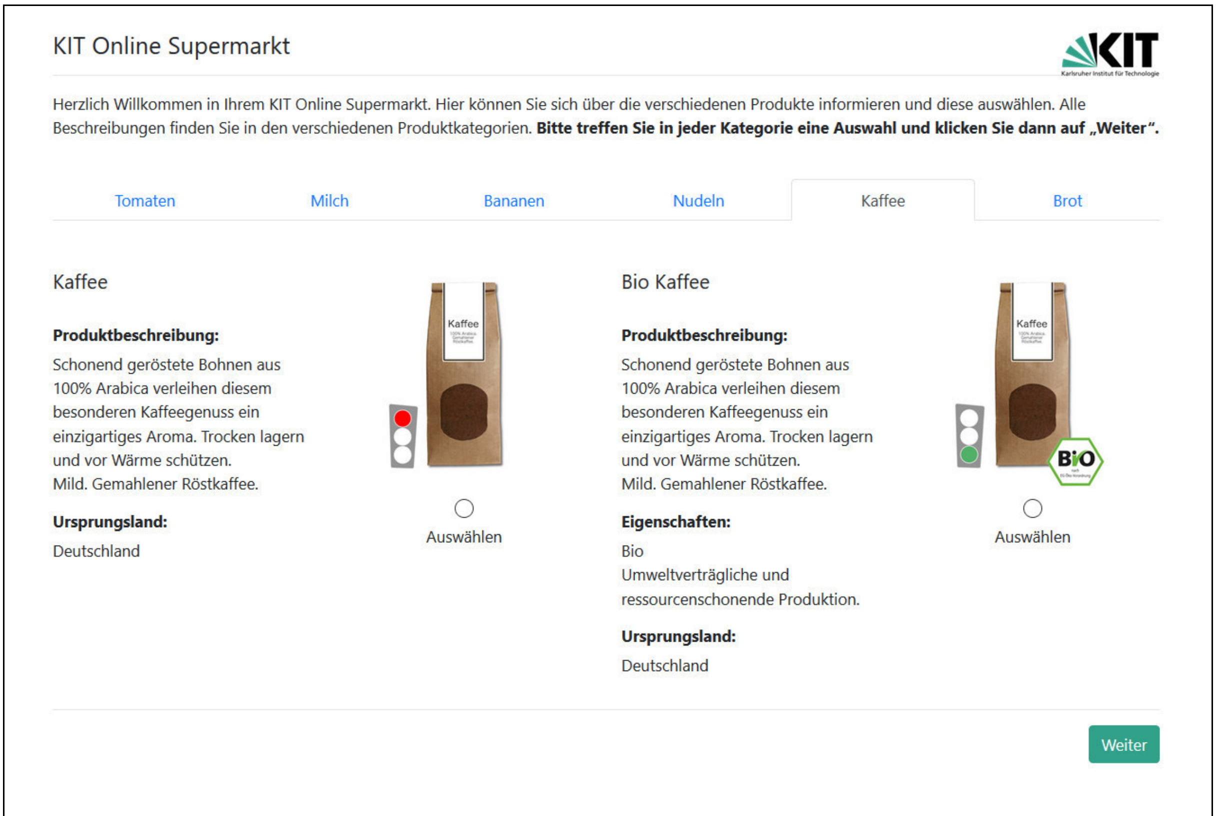

Figure 28. Screenshot of online shop with warnings nudge (Study 4)

Publication List: Dennis Kaiser (geb. Hummel)

Peer-reviewed publications

Hummel, D., Toreini, P. and Maedche, A. (2018). Improving Digital Nudging Using Attentive User Interfaces: Theory Development and Experiment Design. *Research in Progress Proceedings of the 13th International Conference on Design Science Research in Information Systems and Technology (DESRIST)*, 1–8.

Hummel, D., Herbertz, S., and Maedche, A. 2018. "Biological Sex vs. Psychological Gender-Roles in Online Channel Choices: Evidence Form Two Studies in the Financial Services Industry," in *Proceedings of the 4th Conference on Gender & IT - GenderIT '18*, New York, New York, USA: ACM Press, pp. 199–208.

Hummel, D., Schacht, S. and Maedche, A. (2017). Designing Adaptive Nudges for Multi-Channel Choices of Digital Services: A Laboratory Experiment Design. In: *Proceedings of the 25th European Conference on Information Systems (ECIS)*. pp.1–12.

Hummel, D., Schacht, S. and Maedche, A. (2017). Multi-Channel Choice in Retail Banking Services: Exploring the Role of Service Characteristics. In: *13th International Conference on Wirtschaftsinformatik*. pp.619–633.

Hummel, D., Schacht, S. and Maedche, A. (2016). Determinants of Multi-Channel Behavior: Exploring Avenues for Future Research in the Services Industry. In: *Proceedings of the 37th International Conference on Information Systems (ICIS)*. pp.1–12.

Papers under review

Hummel, D., Vogel, T., Schacht, S. and Maedche, A. (2018). From the Why to the Who in Channel Choices: The Role of Personality Traits and Gender Roles to Individualize Digital Channels. *Under review in European Journal of Information Systems*, 1–24.

Hummel, D. and Maedche, A. (2018). How Effective Is Nudging? A Quantitative Literature Review on the Effect Sizes and Limits of Empirical Nudging Studies. *Under review in Journal of Behavioral and Experimental Economics*, 1–29.

Working papers

Hummel, D., Vogel, T. and Maedche, A. (2018). Individualized Digital Nudges for Sustainable Product Choices in Digital Retail Channels: The Moderating Role of Personality Traits. *Working Paper*, 1–32.

Practice oriented publications

Hummel, D., and Maedche, A. 2017. “IT-Trends in Der Finanzbranche,” *HI:TECH CAMPUS It* (2), pp. 32–35.

Eidesstattliche Versicherung

gemäß § 6 Abs. 1 Ziff. 4 der Promotionsordnung des Karlsruher Instituts für Technologie für die Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema *Individualized Choices and Digital Nudging: Multiple Studies in Digital Retail Channels* handelt es sich um meine eigenständig erbrachte Leistung.
2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.
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Karlsruhe, den 10.10.2018

Dennis Hummel