Products and Services in the Digital Age: Findings of a Multi-Perspective Approach

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Für meine Eltern und meinen Bruder

Abstract

The digitalization has prompted numerous changes in business and society. These changes can be witnessed, for example, in the increasing transformation of products and services, which in turn raises exciting questions for research in management. The aim of this cumulative dissertation is therefore to tackle some of the most pressing issues in current management research in order to shed light on some of the conceptual and behavioral peculiarities underlying the intertwined digitalization of products and services. Overall, this anthology consists of three interrelated but independent research essays which revolve around the overarching topic *Products and Services in the Digital Age*. Each essay looks at the topic from a unique perspective and addresses different research gaps on the basis of distinct underlying data.

The first essay is conceptual in nature and is based on data gathered from the Web of Science Database (WoS). The second essay is based on empirical data that was collected in the facilities of the TIME Research Area at the RWTH Aachen University and via Amazon Mechanical Turk as well as social media channels. The data for the third essay was gathered in the facilities of the RWTH Aachen University behavioral lab (AIXperiment lab) and via Amazon Mechanical Turk (MTurk).

Essay I sheds light on the different understandings of Smart Products in current research. Presently, there is no consensus regarding the definition of a Smart Product. Thus, extant literature suffers from the fact that studies rely on varying and partly conflicting conceptualizations, which has led to a rather scattered and patchy body of literature with unclear language and conceptual boundaries. This limits comparability across studies and hinders the incorporation of the Smart Product into related concepts such as the *Internet of Things* (*IoT*) or *Smart Services*. There is thus a need to take stock of extant articles and develop a common language that allows for cumulative research and, consequently, supports a more structured advancement of the field. To this end, first, existing articles on Smart Products were reviewed across contributing disciplines by means of a systematic literature review (SLR). This led to an overview of the status quo, that is, an initial set of criteria that are currently applied to characterize “Smart Products”. Using systematic coding, these criteria were standardized into 19 defining criteria within a 5-level hierarchy. After that, a bibliometric

analysis was performed to reveal structural patterns underlying the current literature, allowing deeper insight into the nature of the diverse understandings of “Smart Products” within and across disciplines. In summary, this study contributes to improving the understanding and conceptual clarity of the *Smart Product*, paves the way for more cumulative research advancements and puts forth implications for practice.

Essay II explores the phenomenon of resistance to Smart Products. Despite their positive and useful facets, consumers' feelings with regard to Smart Products may not always be entirely positive which can lead to consumer resistance. This urges research to gather specific knowledge about the underlying beliefs and suspicions that may cause resistance. This study examines resistance in the context of a cutting-edge Smart Product, the intelligent assistant. The overall purpose of this *mixed-methods* study is twofold. The first study seeks to open the black box of people's minds by employing a mental model study to comprehensively scrutinize belief structures that may promote resistance with a particular interest in revealing hitherto unknown and technology-specific inhibitors to intelligent assistants. The second study aims to dive deeper into the thus identified inhibitors by testing them in a contextualized research model using a quantitative study. The results from this study provide valuable starting points to tackle potential resistance to AI-empowered household technology as well as bear the potential to spark fruitful discussions in research related to AI-empowered consumer technologies in general.

Essay III explores the potentially harmful impacts of robo-advice on service relationships. Professional service firms across different industries are increasingly replacing human advice by robo-advice. However, robo-advice might not capture the social dimension of advice, which may harm existing relationships. Three studies show that stand-alone robo-advice, one of the most common types of robo-advice, reduces the relationship quality compared to a combination of human and robo-advice (i.e., hybrid robo-advice). Moreover, it has been demonstrated that this effect is dependent on the type of relationship customers have with a service provider. When customers have a communal relationship with a service provider, stand-alone robo-advice is more harmful than hybrid robo-advice, as stand-alone robo-advice violates communal relationship norms. In contrast, when customers have a mere exchange relationship with a service provider, they are more open to stand-alone robo-advice as they do not perceive a violation of relationship norms. An additional experiment also shows that robo-advice which mimics human social behavior may backfire by further reducing relationship quality. These findings emphasize the incompatibility of marketing initiatives to promote communal relationships and robo-advice. In addition, they demonstrate how managers should introduce robo-advice while avoiding harmful effects on their customer relationships. Additionally to its relevance for practice, the findings from this study offer valuable insights for the scientific discourse related to the application of AI in services at large.

Zusammenfassung

Die Digitalisierung hat zu zahlreichen Veränderungen in Wirtschaft und Gesellschaft geführt. Diese Veränderungen zeigen sich beispielsweise in der zunehmenden Transformation von Produkten und Dienstleistungen, was wiederum spannende Fragen für die Managementforschung aufwirft. Ziel dieser kumulativen Dissertation ist es daher, einige drängende Fragen der aktuellen Managementforschung zu adressieren, um konzeptionelle und verhaltensbezogene Besonderheiten zu beleuchten, die der Digitalisierung von Produkten und Dienstleistungen zugrunde liegen. Insgesamt besteht diese Dissertation aus drei miteinander verbundenen, aber unabhängigen Forschungsaufsätzen im Kontext des übergreifenden Themas *Produkte und Dienstleistungen im digitalen Zeitalter*. Jeder Aufsatz greift dieses Thema aus einer besonderen Perspektive auf und beleuchtet auf Grundlage unterschiedlicher Daten Forschungslücken.

Der erste Aufsatz ist konzeptioneller Art und basiert auf einer systematischen Literaturanalyse, die anhand der Web of Science (WoS) Datenbank durchgeführt wurde. Der zweite Aufsatz basiert auf empirischen Daten, die in Einrichtungen der TIME Research Area der RWTH Aachen University, über Amazon Mechanical Turk sowie sozialen Medien gesammelt wurden. Die Daten für den dritten Aufsatz wurden in den Einrichtungen des Behavioral Lab (AIXperiment Lab) der RWTH Aachen University und über Amazon Mechanical Turk (MTurk) gesammelt.

Der erste Forschungsaufsatz dieser Dissertation beleuchtet die unterschiedlichen Definitionsansätze zu Smart Products, die in der gegenwärtigen Forschungslandschaft kursieren. Aufgrund des schnellen technischen Fortschritts im Bereich smarter Technologien sowie der Interdisziplinarität der Forschung fehlt aktuell ein übergreifender Konsens darüber, was das Smart Product als Untersuchungsgegenstand auszeichnet. Dies macht sich in der aktuellen Forschung dadurch bemerkbar, dass sich Studien auf unterschiedliche und teilweise widersprüchliche Konzeptualisierungen stützen, was das Forschungsfeld an seine sprachlichen und konzeptionellen Grenzen geführt hat. Darüber hinaus schränkt dieser fehlende Konsens die Vergleichbarkeit zwischen bereits durchgeführten Studien ein und erschwert die Bezugnahme zu verwandten Konzepten wie beispielsweise *Internet of Things* (*IoT*) oder *Smart Services*. In einer solchen Situation ist es unerlässlich, eine

Bestandsaufnahme der bestehenden Forschungsarbeiten vorzunehmen, um auf dieser Grundlage eine einheitliche Terminologie zu entwickeln, die eine kumulative Entwicklung der Forschung unterstützt und folglich einen strukturierteren Aufbau des Wissensstands ermöglicht. Aus diesem Grund wurde die bestehende Forschung zunächst aus verschiedenen Perspektiven untersucht. Dies führte zu einer vollständigen Identifizierung der Kriterien, die in der bestehenden Literatur zur Charakterisierung von *Smart Products* verwendet werden. Basierend auf einer systematischen Kodierung wurden diese Kriterien in einem nächsten Schritt in 19 übergeordnete Gruppen innerhalb einer logischen Hierarchie, bestehend aus fünf Ebenen, überführt. Schlussendlich wurde eine bibliometrische Analyse der identifizierten Literatur durchgeführt, um strukturelle Muster in der bestehenden Literatur aufzudecken. Dies ermöglichte es, dem divergenten konzeptionellen Verständnis von Smart Products, sowohl intra- als auch interdisziplinär, noch tiefer gehender auf den Grund zu gehen. Zusammenfassend trägt diese Studie dazu bei, ein besseres konzeptionelles Verständnis für das Smart Product zu schaffen. Auf diese Weise ebnet sie den Weg für die kumulative Wissensentwicklung und zeigt zudem wichtige Implikationen für die Praxis auf.

Aufsatz II untersucht konsumentenseitige Widerstände gegenüber Smart Products. Konsumenten reagieren auf intelligente Technologien oft mit gemischten Gefühlen und nicht immer uneingeschränkt positiv. Die Kernidee des zweiten Aufsatzes dieser Dissertation ist es daher, die „dunkle Seite“ von Smart Products zu beleuchten. Im Allgemeinen haben intelligente Produkte das Potenzial, die Lebensqualität der Menschen durch eine Vielzahl von Anwendungen zu verbessern. Allerdings sind Konsumenten diesen Technologien gegenüber nicht immer durchweg positiv eingestellt. Es gibt durchaus Widerstände vonseiten der Konsumenten, die es notwendig machen, diesbezüglich in spezifischeres Wissen zu investieren. Hierbei sind insbesondere neue, technologiebezogene Treiber von Widerständen, die im Kontext traditioneller Technologien zuvor nicht aufgetreten sind, interessant. Die im Rahmen dieses Projektes durchgeführte *Mixed-Method*-Studie widmet sich einem weitverbreiteten Smart Product, dem Sprachassistenten. Die Studie verfolgt zwei Ziele. In der ersten Studie soll die Gedankenwelt von Personen, die sich in der Vergangenheit bereits bewusst gegen Sprachassistenten entschieden haben, erforscht werden. Dies geschieht anhand einer Untersuchung von *mentalen Modellen*.

Dabei besteht ein besonderes Interesse darin, bisher unbekannte und technikspezifische Widerstandsfaktoren (Inhibitoren) von Sprachassistenten aufzudecken. Ziel der zweiten Studie ist es ferner, die entdeckten Inhibitoren mittels einer quantitativen Studie in einem kontextualisierten Forschungsmodell zu testen. Die Ergebnisse dieser Studie liefern wertvolle Ausgangspunkte, um potenzielle Widerstände gegenüber KI-fähiger Technologie zu bekämpfen und bergen das Potenzial, die Forschung zu KI-fähigen Technologien im Allgemeinen voranzutreiben.

Aufsatz III beleuchtet mögliche negative Auswirkungen von Robo-Advice auf Servicebeziehungen. Professionelle Dienstleistungsunternehmen verschiedenster Branchen ersetzen zunehmend die menschliche Beratung durch Robo-Advice. Allerdings ist Robo-Advice möglicherweise nicht dazu in der Lage, die soziale Dimension einer Beratungsleistung abzudecken, was bestehende Beziehungen beeinträchtigen kann. Drei Studien zeigen, dass *Stand-alone* Robo-Advice, eine der geläufigsten Arten von Robo-Advice, zu einer geringeren Beziehungsqualität führt als eine Kombination aus menschlicher Beratung und Robo-Advice (sog. *Hybrid* Robo-Advice). Darüber hinaus wird deutlich, dass dieser Effekt von der Art der Beziehung abhängt, die Kunden zu einem Dienstleister haben. Bei einer gemeinschaftlichen Servicebeziehung hat der *Stand-alone* Robo-Advice eine negativere Wirkung als das hybride Modell, da er gegen gemeinschaftliche Beziehungsnormen verstößt. Im Gegensatz dazu sind Kunden, die eine reine Austauschbeziehung mit einem Dienstleister pflegen, offener gegenüber Stand-alone Robo-Advice, da sie keine Verletzung von Beziehungsnormen wahrnehmen. Ein zusätzliches Experiment zeigt, dass Robo-Advice, der menschliches Sozialverhalten nachahmt, eine weitere Reduzierung der Beziehungsqualität zur Folge hat. Diese Ergebnisse zeigen somit, dass die Förderung gemeinschaftlicher Geschäftsbeziehungen nicht mit dem gleichzeitigen Einsatz von Robo-Advice zu vereinbaren ist. Darüber hinaus können die Ergebnisse Führungskräften als Orientierungshilfe dienen, um Robo-Advice optimal einzusetzen und somit eine Beschädigung des Dienstleistungsverhältnisses zu vermeiden. Zusätzlich zu ihrer praktischen Relevanz können die Ergebnisse dieser Arbeit Diskussionen in der Forschung im Zusammenhang mit der Anwendung von KI im Dienstleistungsbereich anregen.

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Abbreviations

AI	Artificial Intelligence
B2B	Business-to-business
B2C	Business-to-customer
CMC	Computer-mediated Communication
ECIS	European Conference on Information Systems
EJIS	European Journal of Information Systems
EMAC	European Marketing Academy
HIT	Healthcare Information Technology
IA	Intelligent Assistant
ICT	Information and Communication Technology
IFIP	International Federation for Information Processing
IS	Information Systems
IT	Information Technology
IoT	Internet of Things
JAMS	Journal of the Academy of Marketing Science
JPIM	Journal of Product Innovation Management
JSR	Journal of Service Research
KI	Künstliche Intelligenz
MTurk	Amazon Mechanical Turk
NIST	National Institute for Standards and Technology
NoT	Network of Things
NPD	New Product Development
SLR	Systematic Literature Review
TAM	Technology Acceptance Model
TDIT	Transfer and Diffusion of Information Technology
VHB	Verband der Hochschullehrer für Betriebswirtschaft
WoS	Web of Science

DISSERTATION FRAME TEXT

Products and Services in the Digital Age

Dissertation Part I

1 Introduction

1.1 Problem Orientation

In recent years, advances in information and communication technology (ICT) and artificial intelligence (AI) have fostered the digitalization of products and services. This development has spawned profound changes in various areas of business and society (Huang & Rust 2018; Rust & Huang 2014; Shim et al. 2019). In the dawn of the Internet of Things (IoT) era, AI-driven Smart Products e.g. intelligent assistants (IA) like Amazon's Echo or Alphabet Inc.'s Google Home have found their way into people's homes and offer them assistance through a variety of digitally enabled, fine-tuned personalized services (Ng & Wakenshaw 2017; Huang & Rust 2018; Dawar & Bendle 2018). In some branches, companies have already initiated the digitalization and automation of traditional service jobs by replacing humans with AI-enabled service robots (Baker & Dellaert 2017; van Doorn et al. 2017). This can be observed, for example, in the field of legal or financial services where Dentons, one of the largest US law firms, has launched the legal advisor app ROSS or Deutsche Bank which has introduced the investment robo-advisor ROBIN (Postinett 2016; Schneider 2017). As demonstrated by these examples, the emergence of physical Smart Products is closely intertwined with the digital transformation services (Marinova et al. 2017).

Sparked by the increasing utilization of the above-mentioned technologies in practice, questions concerning the digitalization of products and services have recently played a key role in management research. So far, extant research – although still in its infancy – is highly diverse, interdisciplinary and is developing at a fast pace. In order to keep up with the blistering pace of technological developments, the scientific community is increasingly organizing itself around topic-specific conferences (e.g., Pre-ECIS IFIP WG 8.6 International Working Conference on "Smart Working, Living and Organising" 2018), special journal issues and perspective pieces (e.g., Appio et al. 2018; Gu et al. 2019; Bstieler et al. 2018), and conference panels (e.g., Te'eni et al. 2019) to create a strong research focus for topics revolving around the IoT, smart technologies and AI. This focus has created a "pull effect" resulting in many research endeavors within the management sub-disciplines *Information Systems* (*IS*), *Marketing* and *Innovation*.

However, digitalization also increases the diversity of problems with which research is confronted (Grover, Carter & Jiang 2019), thus, many questions related to the digitalization of products and services are yet to be answered and numerous research gaps remain (Appio et al. 2018; Bstieler et al. 2018). Moreover, the rapid pace of technological progress coupled with the multitude of possible research perspectives complicate the implementation of structured research agendas. However, especially in such fast-pace and emerging research fields, it is important to regularly take stock, marshal and challenge existing knowledge as well as apply new theories and methods (Yadav 2018). Thus, the leitmotif of this dissertation is to provide answers to some promising research questions by revisiting and consolidating extant knowledge as well as by including fresh perspectives. This guides the underlying agenda of this dissertation with its three contributing essays structured along important and topical facets within the digitalization of products and services: Essay I) the delineation of the Smart Product as an epistemic object; Essay II) the detection and investigation of resistance factors to Smart Product adoption; and Essay III) the study of the impact of robo-advice on customer relationships in digital service encounters.

The three research projects of this dissertation are briefly delineated in the following. Each project is introduced with a relevant anecdote, i.e. comment or statement about the respective project which I received at some point during my dissertation work. These helped me to develop a better feel for the topic and contributed significantly to identifying more specific research directions. In the same way, they are meant to help the reader to comprehend some of the trains of thought and decisive moments during this dissertation work.

First, I would like to present two comments given by a scholar after reviewing a first manuscript of Essay I and by a track editor of the *European Conference on Information Systems* (*ECIS*) 2018 after reviewing an earlier version of the same essay.

> *"In my research, I usually speak of 'IoT devices' or, in the words of Porter and Heppelmann, of 'smart, connected devices' or 'digitally augmented products'"* – Comment by another scholar

> "*The purpose of the paper is to develop a commonly accepted terminology to be used when addressing smart products. All three reviewers agree that this is a good idea given the current discussion about smart products and services. However, reviewer 1 points out that he/she does not believe that a universal single definition is possible, but that a framework of concepts is valuable to*

> *support dialogue about the phenomena. Reviewer 1 misses a thorough problematization that anchors the need for a common definition for smart products. This could be used as a base to introduce the reader more to the phenomena and at the same time ground the need for a common definition*" – Associate editor, ECIS 2018

Against the backdrop of these two statements, the first dissertation project seeks to contribute by putting forth a framework which supports a clear delineation of the Smart Product itself as an *epistemic object*. At present, the concept still suffers from the usual problems of an emerging concept of being "widely used but seldom defined" (Small, Boyack & Klavans 2014, p. 1451). At present, there is a lack of clarity with respect to terminology and distinctiveness from related concepts such as the IoT. Despite a number of studies on specific aspects of the Smart Product, confusion about the general conceptualization prevails and a more general and conceptual discussion is still lacking. As a result, extant academic articles often rely on different and partly conflicting conceptualizations which has led to a convoluted body of literature with unclear language and conceptual boundaries. In addition, extant popular definitions such as the one introduced by Rijsdijk, Hultink & Diamantopoulos (2007), Meyer, Främling & Holmström (2009) or Porter & Heppelmann (2014) have already been relatively long-standing. Hence, considering the rapid advancement of technology, it is time for a revision.

Next is a noteworthy comment that I received from one of the participants during the in-depth interviews of my second research project (Essay II):

> *"It's just the creepy sensation that someone is listening, and I do not know who. However, I am not afraid that someone will find out something specific about me, such as my bank account number. I also do not feel like I'm saying anything that could be useful to someone. It's simply a queasy feeling"* – Anonymous participant

Referring to this statement, it seems that in times when technologies are evolving at an ever-faster pace, people are less and less able to comprehend their full range of functional capabilities which may lead to apprehension and resistance on the part of the consumer. Thus, this dissertation project is dedicated to the often less considered "dark side" of technology acceptance research: resistance. In addition to the fact that resistance is a general matter which companies have to deal with when introducing innovations (Talke & Heidenreich 2014), recent industrial research has explicitly highlighted specific consumer-side barriers with respect to the adoption of smart IoT devices (e.g., Accenture 2016). Moreover, recent academic research has also stressed the importance of shedding light onto the “dark side” and potential consumer concerns and inhibitors which could promote resistance to smart devices (e.g., Bstieler et al. 2018; Shim et al. 2019). Thus, research is well advised to address the issue of resistance and to explore the specific naive understandings and conceptions that people develop with respect to these technologies in order to identify specific resistance factors. In particular, this dissertation project seeks to discover and examine novel and hitherto unnoticed resistance drivers, i.e. inhibitors to a cutting-edge Smart Product, the intelligent assistant. In the past, management research in different technology contexts has benefited greatly from the identification of such technology-specific inhibitors (e.g., Bhattacherjee & Park 2014; Brown, Fuller & Vician 2004; Craig, Thatcher & Grover 2019).

The last comment was made by an anonymous study participant during a qualitative pre-study of the third research project (Essay III):

> *“For me, the personal aspect of my financial advisor is very important. I've known him for 20 years now – he’s a person of trust and that's why I really appreciate the personal contact with him. He can support me when I have questions and offer me specific products that precisely meet my needs”* – Anonymous bank customer

Essay III focuses on robo-advice, a self-service technology in digital service encounters which provides personalized advice based on artificial intelligence (AI). Robo-advice is especially prominent in the financial services industry, in which renowned banks and brokers such as Bank of America, Comdirect, or Deutsche Bank have launched robo-advisors that recommend portfolio strategies and develop investment plans for customers. However, professional service firms from other industries, including healthcare and law, are also starting to automate advice. With AI rapidly progressing, one may anticipate that financial robo-advice and similar self-services (e.g., robo-doctors, robo-lawyers) will increasingly outperform humans in services and may therefore pose a threat to traditional service jobs. Moreover, scholars and practitioners have argued that customers could benefit from robo-advice, as it might lead to better results than human advice and may increase service efficiency (Bughin et al. 2017; Marinova et al. 2017). However, so far, the verdict on who will win the "human versus machine" battle in professional services is still pending as it is not yet fully understood how customers respond to robo-advice. As highlighted by the interview statement above, many bank customers have a bank advisor whom they have known personally and trusted for a long time and with whom they greatly appreciate their personal interaction. Thus, to date, it remains unclear how the introduction of service robots may affect the social norms that underly such existing service relationships and, ultimately, the quality of service relationships. Hence, Essay III examines the conditions under which different types of robo-advice may be harmful or advantageous for service relationships.

In summary, this dissertation attempts to provide answers to some promising questions related to the interconnected digitalization of products and services. Due to the interdisciplinarity of the general topic of this dissertation (Ng & Wakenshaw 2017), the three essays of this dissertation are positioned along with the different management sub-disciplines *Innovation Management* (Essay I), *Information Systems* (IS) (Essay II), and *Service Marketing* (Essay III).

1.2 Structure of the Dissertation and Reading Information

The following sections provide an overview of the overall structure of the dissertation. This dissertation is an essay-based cumulative dissertation consisting of three interrelated but independent research essays under the overarching topic *Products and Services in the Digital Age*. The three essays of this dissertation were submitted to peer-reviewed journals before the dissertation frame text was written. Therefore, some of the most recent academic papers cited in the frame text may not be contained in the essays. Moreover, few text passages of the three essays and the frame text may overlap. However, the chapters from the frame text contain additional information and literature which is due to the fact that the essays were restricted by the page and word count limits of the respective journals.

The overall structure of the dissertation is depicted in Figure 1. It is comprised of two parts, whereby the frame text constitutes the first part (5 chapters) and the three research essays the second part.

The first part of this dissertation begins with chapter 1 which introduces the general topic and includes the problem orientation as well as a description of the topic's relevance. Chapter 2 discusses the broader context within which the three research papers are embedded, outlines recent developments and pinpoints some promising research issues. Chapter 3 presents the specific research gaps and the derived research questions for each of the three essays that constitute this dissertation. Chapter 4 presents summaries of the three essays included in this dissertation. It delineates the overall motivation, the chosen research approach as well as the main results of the respective articles. Finally, chapter 5 concludes with a summary of the main contributions of each of the respective essays.

The second part of this dissertation comprises the following three research essays: (1) *Smart Products – No More than an Elusive Idea? Conceptual Review, Synthesis, and Research Directions*, (2) *“Wait, That’s Creepy!” A Mixed-Methods Study on Resistance to Intelligent Assistants*, and (3) *Do Service Robots Harm Service Relationships? Examining the Effects of Robo-Advisors on Relationship Quality*.

Please note that the three individual essays follow the author's instructions of the respective journals to which they were submitted or for which they were considered.

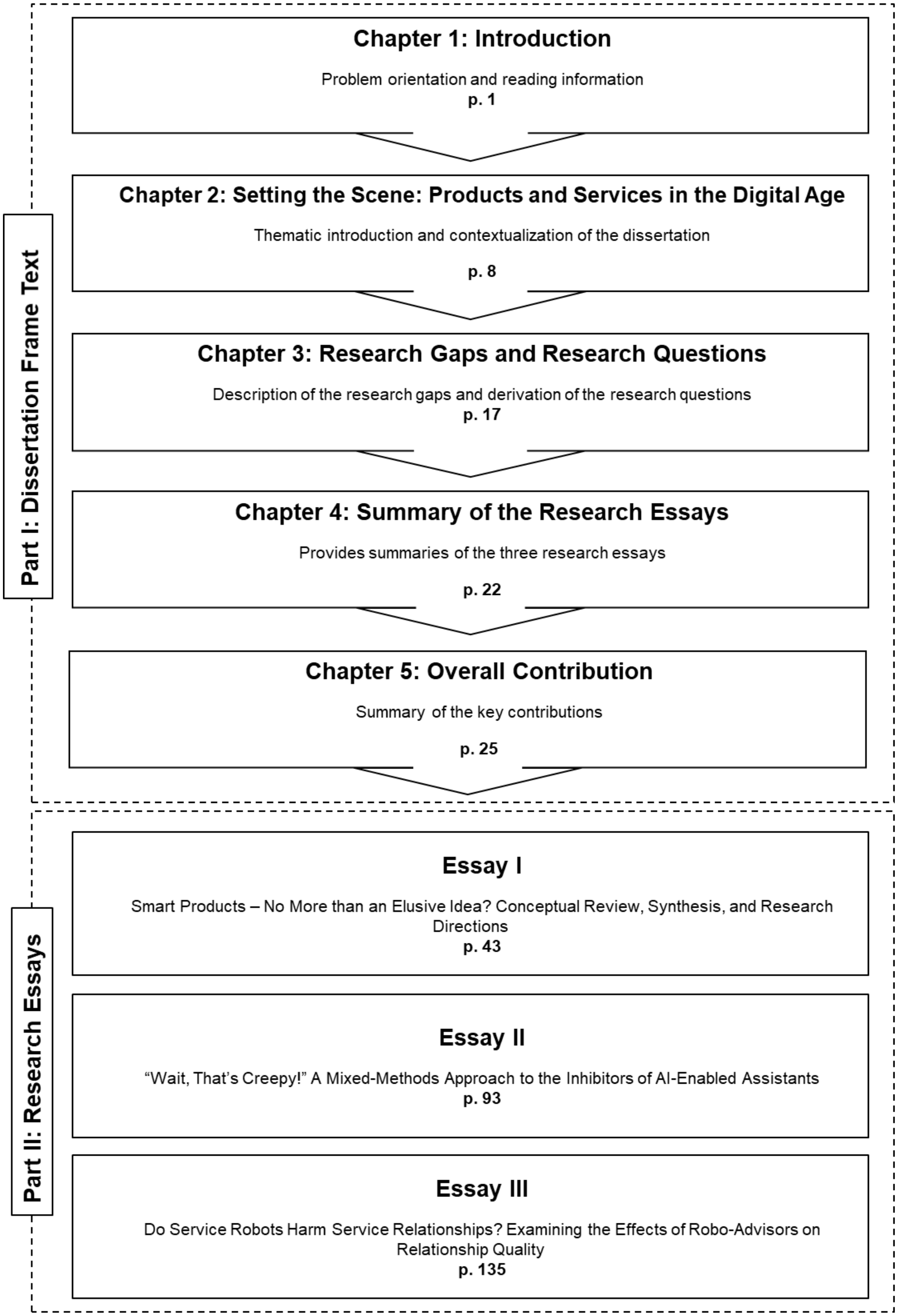

Figure 1. Structure of the dissertation

2 Setting the Scene: Products and Services in the Digital Age

This chapter sets the scene for the three research essays of this dissertation and should help the reader to contextualize the different research essays. The first section discusses the digitalization of products and derives current issues for research. The subsequent chapter establishes the link between Smart Products and digitalization in the services sector as well as discusses the latest advances and developments in the services sector, some of which raise important questions for research.

2.1 Digitalization of Products

2.1.1 The Smart Product in Current Research and Practice

The increasing equipment with sophisticated information technology has led to a transformation of products over the last years and has prompted a new type of product: the *Smart Product* (Rijsdijk, Hultink & Diamantopoulos 2007). From a technical perspective, Smart Products are devices “that contain Information Technology (IT) in the form of, for example, microchips, software, and sensors and that are therefore able to collect, process, and produce information” (Rijsdijk, Hultink & Diamantopoulos 2007, p. 341). With the rise of the *IoT*, which refers to a larger network of smart physical devices that communicate with other entities (e.g., consumers, other systems, services, and devices) via the Internet (Shim et al. 2019; Ng & Wakenshaw 2017; Novak & Hoffman 2018), the Smart Product is steadily increasing and has attracted much attention among consumers but also in management research. In addition, for some time now, more and more devices empowered by added AI have been entering the stage, making AI a crucial building block of Smart Products (e.g., Nest Learning Thermostat).

Extant research on the Smart Product concept is strongly interdisciplinary and has examined Smart Products from a multitude of perspectives including *digitalized interactive platforms* (Ramaswamy & Ozcan 2018), *consumer-object relationships* (Novak & Hoffman 2018; Schweitzer et al. 2019), *connectivity* (Touzani et al. 2018; Verhoef et al. 2017), *autonomy* and *automation* (Schweitzer & van den Hende 2016; Souka et al. 2019; Leung, Paolacci & Puntoni 2018), *general consumer perceptions* (Raff & Wentzel 2019; Rijsdijk & Hultink 2009), *acceptance* and *adoption* (Wunderlich, Veit & Sarker 2019; Schill et al. 2019), *customer relationships, engagement* and *loyalty* (Moriuchi 2019; Dawar & Bendle 2018), as well as *inhibitors* and *resistance* (Mani & Chouk 2017; Mani & Chouk 2018; Raff & Wentzel 2019).

Generally, smart technology disrupts both industrial processes and consumers' routines. For industry, Smart Products bring about various changes along the entire value chain, e.g. in product design, manufacturing, marketing, retailing and after-sales service (Porter & Heppelmann 2014). In addition, Smart Products pave the way for efficiency gains across different processes and enable new service-based business models (Allmendinger & Lombreglia 2005; Wünderlich, Wangenheim & Bitner 2012). An example for the advantageous use of smart technologies in the industry is *remote control* and *remote maintenance*; for example, the integration of sensors and an internet connection in printing presses has allowed Heidelberger Druckmaschinen to offer its maintenance services in a more cost-efficient way (Allmendinger & Lombreglia 2005). Moreover, so-called smart factory concepts offer many opportunities for companies to optimize the efficiency of their production processes through embedded smart technology (Lucke, Constantinescu & Westkämper 2008). For consumers, Smart Products offer many new usage possibilities in their everyday lives, and there are countless examples of Smart Products that are already proving popular. These include Ralf Lauren's intelligent athlete shirt, which allows athletes to track various body functions and motion data, Amazon's intelligent Echo assistant, which supports the user throughout the day with a variety of tailored services, or the Nest Learning Thermostat which is equipped with AI and machine learning capabilities in order to provide the customer with an optimal indoor climate (Novak & Hoffman 2018; Porter & Heppelmann 2014).

As shown by the above examples, however, the multitude of possible applications and contexts for intelligent technologies also means that technically very different products are often summarized under the same collective term *Smart Product* in extant research. Among scholars, the term is oftentimes used as a rather blurry blanket term to refer to inherently very different technology products with very different capabilities such as robots, the Amazon Dash Button, or the autonomous car (see for example Novak & Hoffman 2018; Schweitzer & van den Hende 2016; Rijsdijk & Hultink 2009). In addition, the fact that product smartness may exist in different forms and to different degrees is rarely addressed (for an exception see Novak & Hoffman 2018). Despite the widespread use of the term in current research, there are few more precise and finer-grained definitions of Smart Products that have been consistently applied over time and that allow different Smart Products to be distinguished from each other as well as linked/integrated with other related concepts (few exceptions are Porter & Heppelmann 2014; Rijsdijk & Hultink 2009; Rijsdijk, Hultink & Diamantopoulos 2007). In addition, compared to other precise conceptualizations, such as for *cloud computing* or the *network of things (NoT)*/*IoT* established by the *National Institute for Standards and Technology* (*NIST*) (Voas 2016; Mell & Grance 2011) which management research has adopted and greatly benefitted from (see e.g., Marston et al. 2011; Woodside & Sood 2017), there exists no such thing for the Smart Product concept. Moreover, although in earlier days there had been some attempts to derive and establish a consensus definition in some domains (e.g., Gutierrez et al. 2013) these have neither been able to prevail in the long term nor have they found consistent application across different management disciplines. Now that technology and time have significantly progressed further, the consequences for the research landscape are becoming more and more serious and a sound conceptual basis is needed more than ever. Overall, two major sub-problems can be distinguished.

First, there is no consensus regarding the *conceptualization* and *defining criteria* of the Smart Product. One of the more popular conceptualizations of the Smart Product was introduced by Rijsdijk, Hultink & Diamantopoulos (2007) in *JAMS* (and then slightly adapted in *JPIM* by Rijsdijk & Hultink (2009)). According to the authors, a Smart Product is characterized by the seven dimensions *autonomy*, *adaptability*, *reactivity*, *multifunctionality*, *ability to cooperate*, *humanlike interaction*, and *personality*, as well as “the extent to which it possesses each of these dimensions” (p. 342). While some papers from the fields of information systems (IS), marketing and innovation management rely on or at least refer to this definition for their work with Smart Products (Herterich & Mikusz 2016; Kuijken, Gemser & Wijnberg 2017; Schweitzer & van den Hende 2016; Valencia et al. 2015), other researchers use different definitions or defining criteria when doing research on the concept (e.g., Mayer et al. 2011; Meyer, Främling & Holmström 2009; Wangenheim, Wünderlich & Schumann 2017) or come up with their own ad-hoc conceptualizations (e.g., Whitmore, Agarwal & Da Xu 2015). Other alternative conceptualizations were proposed by Porter & Heppelmann (2014) and Wong et al. (2002). Porter and Heppelmann (2014) characterize Smart Products as a combination of the three core elements *physical components*, *smart components*, and *connectivity components*. Additionally, the authors postulate that Smart Products are enabled by the information technology (IT) that is embedded in physical objects, such as sensors, processors, software implementation, and connectivity modules that allow the storage of captured data in a product cloud. Wong et al. (2002) describe an intelligent product as “one that has part or all of the following five characteristics: 1. Possesses a unique identity, 2. Is capable of communicating effectively with its environment, 3. Can retain or store data about itself, 4. Deploys a language to display its features, production requirements etc., 5. Is capable of participating in or making decisions relevant to its own destiny” (p. 7).

Second, since its emergence scholars have established a variety of terms that are used more or less synonymously for Smart Product. To name but a few: Kortuem et al. (2010), Novak & Hoffman (2018) and López et al. (2011) discuss *smart objects*, while Touzani et al. (2018) refer to *connected objects*, and Ng & Wakenshaw (2017) introduce the term *internet-connected constituents*. Moreover, Tarafdar & Tanriverdi (2018) refer to *IT-embedded, Internet-enabled products*, Herterich & Mikusz (2016) suggest the term *digitized artefact*, whilst Miorandi et al. (2012) prefer the term *smart thing* and, lastly, Meyer, Främling & Holmström (2009) use the term *intelligent product*. There are even studies which use a mixture of these terms within the same paper without clearly differentiating one from another (e.g., Dawid et al. 2017; Mani & Chouk 2017; Porter & Heppelmann 2014). Problematically, very few authors explicitly address the existence of different terms in their work (e.g., Kiritsis 2011). This conceptual ambiguity is compounded by the fact that there are other concepts which overlap with the Smart Product but nonetheless need to be clearly distinguished in a conceptual sense (Holler, Uebernickel & Brenner 2016). Prominent examples are *ubiquitous computing*, *ambient intelligence*, and above all the *Internet of Things* (*IoT*) (Oberländer et al. 2017).

Overall, the current body of knowledge on Smart Products is built on an unstable foundation. The rapid upsurge of the concept paired with its inherently interdisciplinary nature has led to a lack of consensus as to what exactly defines the Smart Product. Hence, despite its popularity-in-use and compelling calls for research, the Smart Product itself remains an elusive idea rather than a clearly defined epistemic object (Alter 2019; Rheinberger 1997). Against this background, it becomes clear that the repeated calls for a debate on Smart Products and related topics (e.g., Barczak 2016; Bstieler et al. 2018) can only be fruitful if there is clarity about the Smart Product itself. Thus, in light of such a young, fast-moving and rapidly evolving field, it is important to take a step back and to first address this issue in order to create a timely consensual basis for future research initiatives.

2.1.2 The "Dark Side"

In addition to the lack of a clear conceptual understanding for the Smart Product concept, some of the underlying psychological particularities which guide their general acceptance remain largely unexplored and require further research (Shim et al. 2019; Wunderlich, Veit & Sarker 2019). There seem to be a crossroads. On the one hand, it cannot be denied that the advances in technology offer many splendid opportunities for business and society. Part of the reality, on the other hand, is also the fact that the diffusion and adaptation of these technologies is progressing at a much slower pace than expected in many areas (Accenture 2016; Mendling et al. 2018). Recent research with respect to smart consumer technologies claims that consumers' feelings and conceptions are not always entirely positive, which may lead to resistance (e.g., Cremer, Nguyen & Simkin 2017; Mani & Chouk 2017; Raff & Wentzel 2019; Ransbotham et al. 2016). Apparently, there are still many doubters and sceptics who hold negative conceptions about these disruptive technologies which may ultimately drive resistance.

Moreover, a series of negative incidents and criticism expressed by famous public figures in recent months and years may have fuelled this scepticism. To name but a few: in 2018, it became known that Amazon Echo devices had recorded a family's conversation and then sent it to their private contacts (Bond 2018). In addition, a technical error in early 2018 caused Amazon Echo to launch a series of unwanted actions, such as suddenly broadcasting creepy laughter or listing local cemeteries and funeral parlors which frightened a large number of users (Segarra 2018). Furthermore, famous public figures such as Tesla founder Elon Musk or academic celebrity Stephen Hawking warned of the general dangers and threats associated with AI-empowered technologies (Johnson & Verdicchio 2017). Stephen Hawking, for example, even proclaimed that the rise of AI could mean the end of the human race (Floridi 2016).

Against this backdrop, research is well-advised to shed light on the entirety of the conceptions, ideas, and beliefs (i.e., mental models) which people hold with respect to smart technologies in order to identify concerns and inhibitors that may lead to resistance (e.g., Bstieler et al. 2018; Shim et al. 2019). It may be expedient to start with inductive-explorative research approaches since the factors driving resistance to smart technology might be original and distinct from those of traditional technologies.

Taken together, it seems a worthwhile endeavor for research to invest in a better comprehension of the specific threat perceptions and negative conceptions underlying resistance to AI-empowered technologies, both in an organizational and consumer-oriented environment (Bstieler et al. 2018; Mendling et al. 2018).

2.2 Digitalization of Services

The digitalization of products is closely entwined with the digitalization of services. In fact, in many cases, the previously outlined digitalization of physical products represents a direct precursor to the increasing digitalization and automation of services (Allmendinger & Lombreglia 2005; Rust & Huang 2014; Marinova et al. 2017). In the scientific community, these developments are also termed *IT revolution* and *service revolution* (Rust & Huang 2014). Similar to Smart Products, the digital revolution in the services industry has given rise to many new research topics. In recent years, scholars have taken a multitude of different perspectives such as *smart services* and *smart service systems* (Wünderlich, Wangenheim & Bitner 2012; Wuenderlich et al. 2015; Demirkan et al. 2015; Beverungen et al. 2019; Barile & Polese 2010), *business strategies* (Allmendinger & Lombreglia 2005), *adoption* (Töytäri et al. 2018), *AI in digital service encounters* (Ostrom, Fotheringham & Bitner 2019; Huang & Rust 2018), *service robots* (van Doorn et al. 2017; Jörling, Böhm & Paluch 2019; Giebelhausen et al. 2014; Baker & Dellaert 2017), and *resistance* (Chouk & Mani 2019).

For some time now, companies have undergone a transformation from purely product-centered to service-oriented companies and have recognized that it is important to offer a variety of value-added services in addition to their physical core product(s), thus, shifting the focus from goods-dominant to service-dominant (Lovelock & Wirtz 2011; Vargo & Lusch 2004). Nevertheless, in times of digitalization, it no longer suffices to simply supplement physical products with a standardized set of added services (Allmendinger & Lombreglia 2005). Through the recent rapid progress in information and communication technology (ICT), e.g. big data, cloud computing and networking technology (Rust & Huang 2014; Wünderlich, Wangenheim & Bitner 2012), products have become increasingly intelligent and, as described in the previous chapter, in many cases are evolving into Smart Products (e.g., Porter & Heppelmann 2014; Rijsdijk, Hultink & Diamantopoulos 2007). This technical progress has transformed service provision both in business-to-business (B2B) and business-to-consumer contexts (B2C) (Rust & Huang 2014; Wünderlich, Wangenheim & Bitner 2012). Likewise, service recipients and their expectations have shifted (Rafaeli et al. 2017). Today, service recipients are no longer satisfied with standardized service solutions but have come to expect highly personalized and intelligent services (Marinova et al. 2017).

Intelligent services or so-called *smart services* are often wrapped around physical *Smart Products* (Allmendinger & Lombreglia 2005). These Smart Products are capable of collecting data via a variety of *smart components* as well as sharing the data with e.g. the manufacturing company or another interconnected Smart Product via *connectivity components* (Porter & Heppelmann 2014). Ultimately, the collected data is interpreted via built-in product intelligence and transformed into a variety of smart services which, for example, provide the user with a very personalized user experience or enable companies to remotely identify and resolve faults through predictive diagnostics before a complaint is received (Allmendinger & Lombreglia 2005; Porter & Heppelmann 2014). As a result of the ever-increasing digitalization in the service domain, completely new business models have emerged throughout the last years which are based primarily on the provision of the previously described smart services (Paluch 2017). Well-known examples are companies such as Amazon, Apple or Fitbit, which obtain large amounts of user data via devices such as the Amazon Echo or the Apple Watch. This data can then be analyzed and translated into fine-tuned personalized smart services (Marinova et al. 2017; Rafaeli et al. 2017).

Another game-changing technological development only recently entered the service domain, namely artificial intelligence (AI) (Buhalis et al. 2019; Huang & Rust 2018). Originally, the concept of AI was raised by McCarthy et al. (1955) and is based on the underlying assumption “that every aspect of learning or any other feature of (human) intelligence can in principle be so precisely described that a machine can be made to simulate it" (p. 12). Today, AI has become a reality and allows a machine to perform cognitive functions that we otherwise only know from humans, such as thinking, learning, problem-solving, or creativity (Rai, Constantinides & Sarker 2019; Huang & Rust 2018). AI itself has gained inflationary popularity-in-use among users, and research across the different management disciplines shows a keen interest in the concept (e.g., Gu et al. 2019; Rai, Constantinides & Sarker 2019; Ostrom, Fotheringham & Bitner 2019; Huang & Rust 2018; Te'eni et al. 2019). Especially the recent editorials (e.g., *Next-Generation Digital Platforms: Toward Human–AI Hybrids*) and call for papers from the *Management Information Systems Quarterly* (*Managing AI*) or the *Journal of Business Research* (*Using Big Data and Artificial Intelligence in Business to Impact Global Challenges*) once more underline the significance of AI in current management research (Gu et al. 2019; Rai, Constantinides & Sarker 2019; Zahir, Love & Kamal 2019).

In the service domain, the *AI revolution* has gained momentum and the use of AI-enabled solutions has already become a reality in some areas, e.g. in the form of AI-enabled service robots (Huang & Rust 2018). That is, for example, virtual service robots such as chatbots that undertake intangible actions in digital service encounters or physical service robots that undertake tangible actions such as serving customers in a restaurant (Wirtz et al. 2018). To date, AI-enabled service robots have already received some attention in recent service research that has been studying them from different viewpoints such as attribution of *responsibility in service encounters* (Jörling, Böhm & Paluch 2019), *service experiences* (Mende et al. 2019) or *general conceptualizations* and *typologies* (Wirtz et al. 2018; van Doorn et al. 2017).

From a more general perspective, three different types of AI application in service encounters can be distinguished: 1) *AI Supported*, 2) *AI Augmented*, and 3) *AI Performed* (Ostrom, Fotheringham & Bitner 2019). *AI Supported* describes an artificial intelligence that works in the background to support a frontline service employee. These may, for example, be tools that can recognize a customer's emotional state and support the service employee in treating the customer accordingly. *AI Augmented* describes a situation in which the AI interacts directly with the customer or is visibly present during the service interaction. In this case, the interaction with the customer is complemented by additional information and services of the AI. This may be the case when nurses and service robots collaborate in patient care settings. *AI Performed* describes the case when the AI-enabled service robot completely replaces the service staff and provides services entirely on its own. Examples include the autonomous delivery of packages by drones or the provision of robo-advice in financial services.

The most thorough way to use AI in services is the third and last of the previously described types, namely *AI performed* service provision, i.e. the complete replacement of the service employee by an AI-enabled robot. The implementation of such AI performed services is encouraged by current research, which recommends that companies should opt for this type of service if it offers (1) either a significant cost advantage or (2) a significant quality advantage, or (3) both (Huang & Rust 2018). In recent years, many professional service firms have started introducing robo-advice, an AI performed self-service technology which replaces human service employees and provides personalized advice. Robo-advice is especially prominent in the financial services industry, in which renowned banks and brokers such as Deutsche Bank or Santander have launched robo-advisors that support customers in their investment decisions (Baker & Dellaert 2017). However, other professional service industries are also increasingly automating advice. For example, Dentons, one of the largest US law firms, has invested in ROSS, a legal adviser app based on IBM Watson (Croft 2016). In China, the Guangzhou Second Provincial Central Hospital was one of the first to offer its patients health consultations and diagnoses via a chatbot (Huang 2018).

Nevertheless, analogously to Smart Products, many of the underlying behavioral and psychological particularities with respect to the acceptance of the outlined types of AI-enabled services remain unexplored and require further research (Ostrom, Fotheringham & Bitner 2019). While robo-advisors are meant to substitute humans in many cases, there is no evidence as to how this might affect service relationships. However, since professional service encounters are primarily social experiences, characterized by a high degree of customer participation and interpersonal exchange, the implementation of robo-advisors may have a significant impact on service relationships (Chan, Yim & Lam 2010).

It is against this background that – from a managerial perspective – it is important to carefully examine the application of robo-advice as well as the underlying behavioral mechanisms and consequential impacts on service relationships. To date, it seems like many companies have introduced robo-advice in a rather unstructured manner without a prior careful assessment of customer needs or possible consequences and impacts on the customer. As a result, many companies fall short of expectations and some, such as Santander, UBS or the asset manager Investec Click & Invest, have already discontinued their expensive robo-advice projects because they were not well accepted by the market (Beioley 2019; Rezmer & Schneider 2019).

Therefore, it is important to take a step back and first create a better understanding of the market and the customer with respect to the different possible applications of intelligent technologies in service frontline interactions (substitution vs. complementary) in order to create solid guidelines for the practical implementation of robo-advice (Marinova et al. 2017). Moreover, it also appears important to understand how customers evaluate the implementation of robo-advisors against the background of their existing service relationships and how robo-advisors affect the quality of these relationships. Furthermore, it might be interesting to explore to what extent customer reactions change if this new technology is not only intelligent but also empathetic in the sense of a *feeling technology* (Rafaeli et al. 2017). In order to support these endeavors, for research it seems worthwhile to link the literature streams on self-service technologies and service relationships and to examine how the application of different types of robo-advice (e.g., robo-advisors that operate on a stand-alone basis or hybrid advisors that are combined with human advice, and robo-advisors with or without artificial social support) impacts service relationships as well as interacts with the different types of relationships that customers may have with service providers (Baker & Dellaert 2017; Rai, Constantinides & Sarker 2019; Clark & Mills 1993).

3 Research Gaps and Research Questions

Starting off from the previously outlined overall context of the work, this section outlines the specifically identified gaps in current research and the derived research questions within the essays that constitute this dissertation.

3.1 Research Gap and Research Questions Essay I

To date, there is neither a consensus definition nor a consistent term for the Smart Product concept which indicates that research on Smart Products may lack cumulative knowledge advancement. Such multifaceted and sometimes conflicting views of concepts are not uncommon as can be seen, for example, in research on *business* *models* or *design thinking* (Foss & Saebi 2017; Micheli et al. 2018). However, since management science is a cumulative venture, the lack of a basic common understanding and precise language severely threatens the development of a cumulative body of knowledge, impedes comparability of empirical findings as well as aggravates the link to other concepts (Astley 1985; Keen 1980; vom Brocke et al. 2009). Consequently, an overarching framework or consensus definition may help structure and baseline present and forthcoming research (Peery 1972). Unless researchers build on each other's work, a research field can never emerge, no matter how good individual fragments may be (Keen 1980). In addition, Klein & Hirschheim (2003) stress the problem of communication deficits between researchers from the field of IS and reference disciplines, while Bstieler et al. (2018) and Mani & Chouk (2018) call for cross-disciplinary research particularly in the field of Smart Products and the IoT. Given the inherently interdisciplinary nature of the field (e.g., Mikusz 2018; Ng & Wakenshaw 2017), this argument is particularly relevant for research on the Smart Product concept. Unless researchers in the field of innovation and related fields like IS and marketing find a common terminological basis and share a specified understanding of Smart Products, an integrated body of knowledge may be slow to emerge (Alter 2018; Klein & Hirschheim 2003). The introduction of such a common terminological basis will enable the scientific community to cultivate pertinent vocabulary that “facilitates ongoing dialog and additional research initiatives” (Yadav 2018, p. 364). Thus, the debate about Smart Products and related topics that was repeatedly called for (e.g., Barczak 2016; Bstieler et al. 2018) can only be fertile if there is clarity and consensus about the concept.

Thus, in service of this endeavor, the first objective of this project is to shed light on current research and the conceptualizations for Smart Products in order to identify the definitions and descriptive elements that are currently applied. Moreover, based on a synthesis and coding of these elements, this project seeks to put forth a standardized and comparable set of defining criteria for Smart Products and derive a consensual framework. Lastly, it aims to highlight relevant issues and tensions in the current literature in order to guide future research and practice.

Overall, this research project is guided by the following research questions:

RQ1. *What is the content of the current academic body of literature investigating Smart Products?*

RQ2. *How can extant research be synthesized towards a set of standardized defining criteria for Smart Products?*

RQ3. *What are the limitations of current research and promising avenues for future investigation?*

3.2 Research Gap and Research Questions Essay II

Despite the promising potential of IA, consumers' responses to Smart Products such as intelligent assistants may not necessarily be positive, which could lead to resistance (Ransbotham et al. 2016; Cremer, Nguyen & Simkin 2017). Traditionally, management has no choice but to deal with innovation failure and consumer resistance, as failure rates of high-tech innovations around 40-50% are consistently reported (Castellion & Markham 2013; Ram 1987). Moreover, Novak & Hoffman (2018) emphasize that the uniqueness of smart technologies requires us to rethink consumer-object relationships. This uniqueness may therefore also require to rethink other facets, for instance, the factors leading to resistance to this new type of artifact. In consequence, these factors may help practice in effectively stimulating the diffusion of IA. Thus, it appears worthwhile to invest in a better comprehension of the psychology underlying resistance to IA (Bstieler et al. 2018; Wirtz et al. 2018).

However, despite the great scholarly interest in IoT in general and IA in particular, little research that has examined these technologies from the perspective of technology resistance. Alongside traditional fears relating to privacy and control, there may be new factors driving resistance (Bstieler et al. 2018; Ostrom, Fotheringham & Bitner 2019). In addition, there may be factors beyond the traditional IS acceptance assessments proposed in the Technology Acceptance Model (TAM) (Davis 1989). As such, models like the TAM exclusively consider those factors that promote technology adoption but neglect those that may inhibit adoption (Bhattacherjee & Hikmet 2007). However, as adoption and usage typically depend on the interplay of both, the enabling and the inhibiting factors, these approaches may not provide a sufficiently holistic picture (Cenfetelli, 2004). Moreover, and above all, most technology acceptance studies run on the assumption of actual experience (e.g., Koufaris 2002; Moriuchi

2019; Strader, Ramaswami & Houle 2007). In many cases, however, the decision to adopt technology is not based on people's actual experiences. Instead, their decisions may be strongly shaped by their *mental models*. These mental models represent the conceptions and beliefs regarding a technology based on what people hear, infer and construe without necessarily correctly and appropriately representing real causalities and conditions (Bagozzi & Lee, 1999; Vandenbosch & Higgins, 1996). Thus, to achieve a deeper comprehension of the nature of people's resistance to IA, it is essential to first explore the complex and sometimes decontextualised inhibiting conceptions that people hold in their mental models (Złotowski, Yogeeswaran, & Bartneck, 2017).

In this essay, we address this gap in the literature. Drawing on research on mental models, active innovation resistance and the dual-factor model of resistance, we examine the adoption decision process for IA with a specific focus on those factors that inhibit adoption. In particular, we focus on the inhibitors that arise when potential customers *actively* reflect on IA and then deliberately decide against adoption. Unlike more *passive* forms of innovation resistance (e.g., status-quo satisfaction), these inhibitors arise from the innovation itself and take effect when the consumer actively reflects on them (Heidenreich & Kraemer, 2016).

Taking a mixed-method approach by combining an inductive, exploratory study and a deductive, explanatory study, this dissertation project investigates the mechanisms underlying the resistance to IA.

The research project is guided by the following research questions:

RQ4. *What are the constructed ideas and beliefs that drive the the resistance to IA? (inductive)*

RQ5. *What are the nomological paths that shape resistance to IA? (deductive)*

3.3 Research Gap and Research Questions Essay III

In professional services, the application of AI-empowered robo-advisors may be a game-changer. However, it is not yet fully understood how customers respond to robo-advice. Professional service encounters are first and foremost social experiences characterized by a high degree of customer participation and interpersonal exchange

(Chan, Yim & Lam 2010). Research has barely considered how AI performed self-service technologies like robo-advisors affect social relationships between customers and service providers (Jörling, Böhm & Paluch 2019). In particular, there is scarce research addressing the question of how the interaction with service robots may affect the social norms that underly service relationships, and, ultimately, the quality of service relationships. It is against this backdrop that it appears important to examine the conditions under which different types of robo-advice may be harmful or advantageous for service relationships.

To address this gap, this project draws on research about advice and social relationships (e.g., Clark & Mills 1993; Dalal & Bonaccio 2010). Specifically, it is argued that interpersonal exchange and social support are essential components of advice-giving and that customers often maintain communal relationships with professional service providers, that is, caring relationships which go beyond mere business relationships (Aggarwal 2009). Following these arguments, it is suggested that introducing stand-alone robo-advice, one of the most common types of robo-advice, violates the social norms underlying communal relationships and may therefore harm the relationship quality. In contrast, offering hybrid robo-advice, that is, placing a human advice layer on top of the automated robo-advice process (Rai, Constantinides & Sarker 2019), may help maintain the relationship quality as it may not violate communal relationship norms to the same extent as stand-alone robo-advice. It is also proposed that robo-advice which mimics human social support (e.g., a robo-advisor expressing solidarity with a customer) may compensate for the perceived lack of human social support in communal relationships and may therefore lead to a higher level of relationship quality than stand-alone robo-advice without any form of social support.

This research project is guided by the following three research questions:

RQ1. *What is the impact of the application of different types of robo-advice on relationship quality?*

RQ2. *How do different types of robo-advice interact with relationship norms perceived by existing customers?*

RQ3. *What psychological constructs mediate the impact of the application of different types of robo-advice on relationship quality?*

RQ4. *Can adding social support mitigate potential negative effects of robo-advice?*

4 Summary of the Research Essays

This section presents a synopsis of the three essays included in this dissertation. It delineates the overall motivation, the chosen research approach as well as the main results of the respective articles. Each of the essays sheds light on a hitherto under-investigated area by addressing the research questions derived in chapter 3. The three essays were written with different co-authors (Essay I with Professor Dr Daniel Wentzel & Dr Nikolaus Obwegeser; Essay II with Professor Dr Daniel Wentzel; Essay III with Dr Benjamin von Walter & Professor Dr Daniel Wentzel).

4.1 Research Essay I: Smart Products – No More than an Elusive Idea? Conceptual Review, Synthesis, and Research Directions

Essay I addresses the lack of a precise and timely delineation of the Smart Product concept in current research. The paper is currently under review in the *Journal of Product Innovation Management* (JPIM) (VHB-JOURQUAL 3: A)[1].

Although a number of research initiatives contribute to the growing body of knowledge on Smart Products, the concept itself has not been clearly defined yet. Consequently, studies rely on different and partly conflicting conceptualizations which are sometimes confused with other concepts such as the *IoT*, *ubiquitous computing* or *smart services*. Overall, this has led to a rather scattered and inconsistent body of literature with unclear language and conceptual boundaries, limiting comparability across studies and impeding the incorporation of the Smart Product into related concepts such as the IoT or smart services. In such a situation, there is a need to take stock of extant articles and to develop a common language that supports more cumulative knowledge advancement and, consequently, enables a more structured progression of the field.

[1] as of September 2019

In this project, the current research was examined from various perspectives in order to uncover the different understandings of Smart Products. First, a sample of extant papers (n = 37) on Smart Products across the contributing disciplines of IS, marketing and innovation management was reviewed by means of a systematic literature review (SLR). This provided an overview of the status quo, that is, an initial set of criteria that are currently applied to characterize “Smart Products”. Using systematic coding, these criteria were standardized into 19 defining criteria within a 5-level hierarchy (see Figure 2). Lastly, a bibliometric analysis was done to reveal structural patterns underlying the current literature which allowed us to dig deeper into the varying understandings of “Smart Products” within and across the contributing disciplines marketing, innovation management, and information systems (IS).

In sum, this study puts forth a hierarchical conceptual framework for the Smart Product and contributes to improving its understanding and conceptual clarity. Moreover, it paves the way for more cumulative research endeavors and carves out implications for practice.

4.2 Research Essay II: “Wait, That’s Creepy!” A Mixed-Methods Study on Resistance to Intelligent Assistants

This essay deals with the “dark side” of Smart Products and seeks to comprehensively elucidate the factors that drive resistance among potential consumers. Earlier versions of the project were presented at the *European Marketing Academy* (*EMAC*) *Annual Conference 2018* and the *Pre-ECIS IFIP WG 8.6 International Working Conference "Smart Working, Living and Organising" on Transfer and Diffusion of IT, TDIT 2018*. The paper is currently under review in the *European Journal of Information Systems* (EJIS) (VHB-JOURQUAL: A)[2].

This essay sheds light on the largely unexplored negative behavioral reactions with regard to Smart Products by focusing on AI-empowered intelligent assistants (IA) (e.g., Amazon Echo). On the one hand, these assistants have the potential to improve people's quality of life and create new opportunities for practice, such as the provision of personalized services. On the other hand, however, consumers’ responses to this

[2] as of September 2019

technology may not necessarily be positive, which could lead to resistance to adopting these technologies. Thus, it is worthwhile to invest in a better comprehension of the psychology underlying resistance to IA.

To this end, a mixed-methods study was carried out. In the first inductive study (n = 10), the aim was to peer into people's minds and scrutinize the belief structures and conceptions of those who previously had actively resisted IA with a special interest in revealing hitherto unknown and technology-specific inhibitors. For this purpose, a mental model elicitation technique based on creative collages coupled with qualitative in-depth interviews was performed. The second deductive study (n = 409) sought to deductively confirm the accuracy and generalisability of our qualitative findings by testing them in a contextualized research model using a quantitative survey. This allowed us to identify the different effects within the developed research model. In addition, the results provided support for the significance of the novel identified inhibitor *feeling creeped out*.

The main results of this project consist of a fine-grained mental model comprising a comprehensive set of inhibitors and a quantitative validation of the nomological paths that determine resistance to IA. For practice, these inhibitors provide valuable starting points for tackling resistance. In addition, the novel factor of feeling creeped out may become increasingly relevant and bears the potential to spark fruitful discussions in research related to AI-empowered technologies at large.

4.3 Research Essay III: Do Service Robots Harm Service Relationships? Examining the Effects of Robo-Advisors on Relationship Quality

This essay focuses on the emergence of service automation and robo-advice in digital service encounters and its impact on the quality of service relationships. The paper is currently under review in the *Journal of Service Research* (JSR) (VHB-JOURQUAL: A)[3].

[3] as of September 2019

Professional service firms are increasingly replacing human advice by robo-advice in fields such as financial planning, medical consultation, or legal advice. It is against this backdrop that Essay III examines how interacting with service robots can affect the social norms underlying service relationships and, ultimately, the quality of service relationships. In doing so, it sheds light on the conditions under which different types of robo-advice (stand-alone robo-advice, hybrid robo-advice) may be harmful or advantageous for service relationships.

Prior research in this field argues that robo-advice fails to capture the social dimension of advice and may therefore have a harmful impact on existing relationships. One quantitative survey and three experimental studies (n_1 = 124; n_2 = 448; n_3 = 205; n_4 = 112) show that stand-alone robo-advice, one of the most common types of robo-advice, reduces the relationship quality compared to a combination of human and robo-advice (i.e., hybrid robo-advice). It has been shown that this effect depends on the type of relationship customers have with a service provider. For example, when customers have a communal relationship with a service provider, stand-alone robo-advice has a more harmful effect than hybrid robo-advice, as stand-alone robo-advice violates communal relationship norms. In contrast, when customers have a mere exchange relationship with a service provider, they are more receptive to stand-alone robo-advice as they do not perceive a violation of relationship norms. Moreover, the last experiment shows that robo-advice which mimics human social behavior may backfire by further reducing the relationship quality.

Overall, the findings from this research project highlight the incompatibility of marketing initiatives to promote communal relationships and robo-advice. In addition, they explain how managers should introduce robo-advice to avoid damaging their customer relations.

5 Overall Contribution

The three essays of this dissertation are designed to contribute to a better understanding of products and services in the digital age by shedding light on some of the conceptual and behavioral peculiarities relevant to the management sub-disciplines of *Innovation Management*, *Information Systems* (*IS*), and *Service Marketing*. To make a significant contribution to research and practice, this dissertation (1) investigates the interconnected digitalization of products and services from different perspectives (e.g., Smart Product as a concept, resistance to/acceptance of Smart Products, service automation, and service relationships), (2) uses a variety of methods (e.g., systematic literature review, bibliometric analysis, qualitative mental models, quantitative survey, and experiments) as well as (3) takes different theoretical stances (e.g., cumulative knowledge creation, resistance theory, advice theory, and social relationship theory). Besides its specific contributions to research and practice, this dissertation contributes at a superordinate level and makes a number of meta-contributions:

First, this dissertation carries out specific studies on immature and in part still embryonic issues in the context of the digitalization of products and services. Such issues represent a myriad of opportunities for the creation of impactful research and knowledge advancement in management research (Yadav 2018; Barczak 2016). Hence, with its comprehensive and timely studies, this dissertation makes a significant contribution to the existing knowledge in management research and lays the foundation for future impactful research endeavors (Yadav 2018). Second, especially Essay II and III counter the trend in current management research to approach digitalization exclusively from the perspective of *technology as a solution* by taking a more critical perspective in the sense of *technology as a cause of problems* (Rowe 2018).

In addition, each individual essay makes further meta-contributions:

Essay I reviews the current body of knowledge by means of an interdisciplinary systematic literature review (SLR). This allowed for marshalling as well as integrating different swathes of knowledge into a state-of-the-art of current research which may serve as a basis for cumulative knowledge creation. Although the importance and significance of such interdisciplinary and systematic assessments have often been highlighted (e.g., Barczak 2017; Ng & Wakenshaw 2017; Palmatier, Houston & Hulland 2018), they have hitherto relatively rarely been applied in the management sub-disciplines marketing and innovation (for exceptions, see Foss & Saebi 2017; Micheli et al. 2018). In addition, Essay I also addresses some imperatives and action items recently highlighted by Yadav (2018) such as facilitating and exploring new phenomena by creating clarity regarding terminology and conceptualization. All in all, Essay I creates a basis for the body of knowledge on Smart Products to, from now onwards, grow in a more organized and structured manner.

Essay II responds to calls for the adoption of new research methods and mixed-methods in the field of IS. Corresponding calls to create pluralistic perspectives through the application of innovative multi-method (e.g., Mingers 2001; Weber 2004) and mixed-method approaches (e.g., Ågerfalk 2013; Te'eni et al. 2015; Venkatesh, Brown & Bala 2013; Venkatesh, Brown & Sullivan 2016) have existed in the field for a relatively long time. In addition, scholars have called for the use of multifaceted-perspectives, particularly in the area of cutting-edge IoT technologies, in order to illuminate the different phenomena in the most holistic way possible (Shim et al. 2019). However, these calls have so far been met with relatively little response among the top IS journals. Thus, this essay does not follow the usual scripts of knowledge development established by many top IS journals but instead uses an innovative approach to counter this trend and push boundaries.

Last, by taking a first look at robo-advice in digital service encounters, Essay III follows the call recently voiced in marketing research to conduct more timely inquiries on emerging phenomena (Yadav 2018). Such an investigation of the “initial conditions” in the early stages of an emerging phenomenon is important in order to avoid a paucity of knowledge regarding fundamental underlying causal mechanisms (Yadav 2018).

In addition to these meta-contributions, this dissertation also enriches the current body of scientific research through a number of specific contributions for research and practice which are derived in the respective research essays (see also Table 1).

First, this dissertation contributes to existing scientific research by standardizing current understandings of the Smart Product and by putting forth a revised, standardized framework of reference (Essay I). The hierarchical framework for Smart Products depicted in Figure 2 helps to support the dialogue and the emergence of a common language about the currently ill-structured concept. At the same time, it leaves enough space to allow for further context- or product-specific refinements if needed. In addition to this and assuming that the scientific community will use this framework in future research endeavors, it may support cumulative knowledge advancement, improve the comparability of empirical findings as well as facilitate the link to and the integration with other concepts such as AI, IoT or smart services (Astley 1985; Keen 1980; vom Brocke et al. 2009).

For practice, the derived Smart Product framework contributes in several ways. First of all, in view of the wave of terminologies and buzzwords that revolve around the topic of digitalization, it may help practitioners navigate the Smart Product world as well as leverage the firm-internal understanding and dissemination of what a Smart Product is. Such frameworks have been of great value for practice in the past (e.g., for *cloud computing* (Liu et al. 2011) or *customer relationship management* (Zablah, Bellenger & Johnston 2004)) as they represent common points of reference and reduce the risk of miscommunication. When the implementation of Customer Relationship Management (CRM) systems was on the rise in companies, practice benefited greatly from such conceptualizations, which in turn facilitated the general understanding and communication (Zablah, Bellenger & Johnston 2004). In addition, the layered structure of the Smart Product framework and the respective defining characteristics can provide starting points from which practitioners can structure use-cases in order to precisely demonstrate the far-reaching potential benefits of Smart Products.

Table 1. Overview of the three essays and their key contributions

	Smart Products – No More than an Elusive Idea? Conceptual Review, Synthesis, and Research Directions (Essay I)	**"Wait, That's Creepy!" A Mixed-Methods Study on Resistance to Intelligent Assistants** (Essay II)	**Do Service Robots Harm Service Relationships? Examining the Effects of Robo-Advisors on Relationship Quality** (Essay III)
Topic	The delineation of the Smart Product as an epistemic object	Consumer resistance to intelligent assistants	Robo-advice in professional services
Management sub-discipline	Innovation Management	Information Systems (IS)	Service Marketing
Theory	Cumulative knowledge creation	Innovation resistance theory	Advice in services and social relationship theory
Method	Systematic literature review, bibliometric analysis	Mixed-methods (mental model and quantitative survey)	Quantitative survey and behavioral experiments
Unit of analysis	The Smart Product concept	Individual consumer/ user	Individual customer
Key contributions for research	▪ A standardized framework of reference to support the scientific discourse about the Smart Product concept ▪ Support for cumulative knowledge creation ▪ Integrated examination of marketing, innovation and IS literature	▪ Identification of inhibitors and enablers to IA ▪ Identification of the novel inhibitor *feeling creeped out* ▪ Integration of the theoretical strands of active innovation resistance and the dual-factor model of resistance	▪ Stand-alone robo-advice is incompatible with communal service relationships, even if addressed by means of social support ▪ Hybrid robo-advice may be able to offset potential harmful impacts of robo-advice on communal relationships
Key contributions for practice	▪ A fine-grained framework of reference ▪ Starting points from which use-cases can be structured ▪ Support for alignments with e.g. third-party certification requirements	▪ The detected inhibitors provide management with starting points to reduce resistance	▪ Service automation and robo-advice are not a panacea as they are not always compatible with relationship marketing ▪ Dominant relationship type of customer needs to be aligned with type of robo-advice

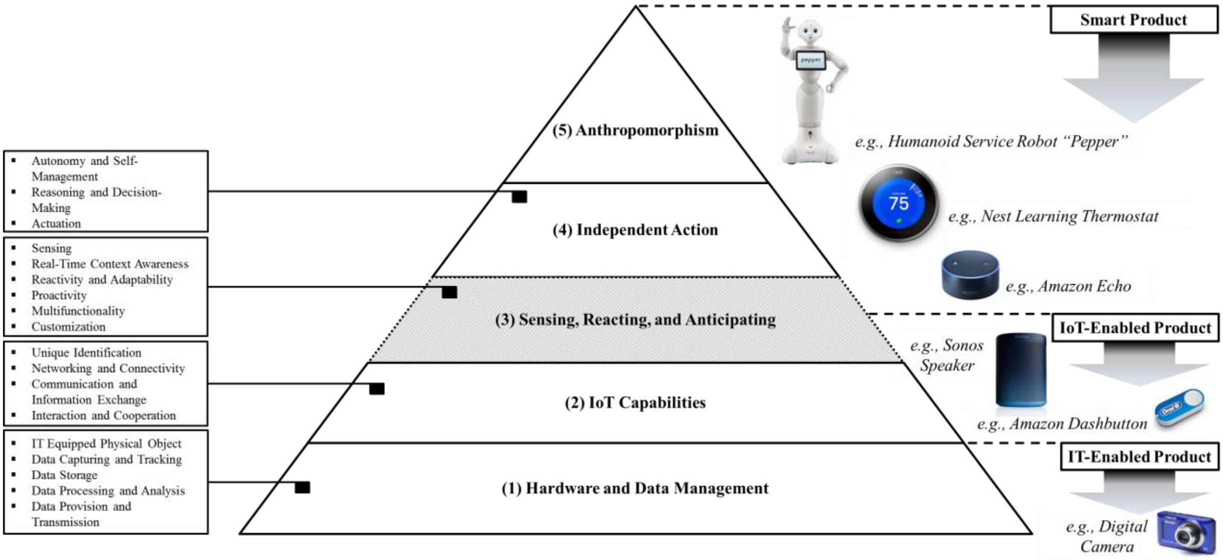

Figure 2. A hierarchical framework for Smart Products

Second, as this dissertation deals with the topic of resistance to intelligent assistants (Essay II), it contributes to scientific research by shedding light on the oftentimes neglected aspect of technology resistance. Using a mixed-method approach, which included an inductive-explorative mental model in the first study, allowed us to identify a range of resistance drivers, i.e. inhibitors, some of which were unknown and are inherent to the nature of smart technologies. For example, we identified the novel aspect *feeling creeped out* which can be distinguished from the previously known creepy/eerie feelings emanating from artificial beings that imperfectly resemble human beings described by the Uncanny Valley Theory (Mori, MacDorman & Kageki 2012). At its core, it is not compulsively linked to aspects of anthropomorphism but rather relates to the conceptualization of creepiness that was established by McAndrew & Koehnke (2016). Due to its significance throughout our explorative mental model study, we positioned it as a novel resistance driver to intelligent assistants. By transferring this aspect from social psychology to a technology context, we created a new link between current research in psychology and information systems (IS) and were able to extend the existing list of known and established resistance drivers with respect to smart or innovative technologies, such as *loss of control* (e.g., Bhattacherjee & Hikmet; Schweitzer & van den Hende 2016) or *privacy risk* (e.g., Ersin & Xin 2017; Lowry, Dinev & Willison 2017). In addition, in the past, IS research has greatly benefitted from the elicitation of technology-specific inhibitors across different contexts such as the *perceived identity threat* in the context of digital technologies in the workplace (Craig, Thatcher & Grover 2019), *switching costs* and *security concerns* in the context of cloud migration (Bhattacherjee & Park 2014), or *loss of control* with regard to healthcare information technology (HIT) (Bhattacherjee & Hikmet 2008). Furthermore, Essay II also contributes by integrating and combining different theoretical strands within resistance theory such as *active innovation resistance* (e.g., Talke & Heidenreich 2014) and the *dual-factor model of technology resistance* (e.g., Bhattacherjee & Hikmet 2007; Cenfetelli 2004). This holistic theoretical underpinning allowed us to comprehensively explain the underlying mechanisms of resistance to intelligent assistants and at the same time proposes an alternate, more holistic lens in the study of technology acceptance.

For practice, our identified inhibitors help explain why people resist or fear AI-empowered household technologies. Our inhibitors thus provide companies with potential starting points for product design that may allow them to reduce resistance in potential customers. In particular, the novel aspect *feeling creeped out* may represent an aspect that companies were not aware of but which may increasingly become relevant in times where technology products differ significantly from those previously marketed.

Third, this dissertation contributes to the current scientific research in services (Essay III). Our research is among the first to examine the impact of robo-advice in different relationship contexts. As such, recent calls for research into the acceptance of new technologies in frontline services have not considered the relational aspects that may be affected by the introduction of such technologies (e.g., Ostrom, Fotheringham & Bitner 2019). However, this dissertation suggests that it is vital to consider the relational effects of self-service technologies. Specifically, it was found that although self-service technologies like robo-advice may lead to efficiency gains in service provision (e.g., Bitner, Brown & Meuter 2000), they may also have a negative impact on relationship quality. Moreover, our findings indicate that the automation of advice may have detrimental effects in industries where customers frequently have communal relationships with their service providers, such as healthcare (van Doorn et al. 2017). Specifically, our results show that stand-alone robo-advice is incompatible with the characteristics of communal service relationships (e.g., care, mutual support), even if these characteristics are addressed via artificial means such as social support.

Our studies further show that only hybrid robo-advice solutions may be able to offset the potentially harmful impact of robo-advice on communal relationships. Artificial social support, in contrast, may further reduce rather than increase relationship quality compared to stand-alone robo-advice. In sum, our findings offer an empirical justification for service providers to introduce hybrid robo-advice to their customers instead of stand-alone robo-advice.

Last, the findings of Essay III contribute to practice in multiple ways. First, they show that, if incorrectly applied, robo-advice may harm existing service relationships. This brings about the important implication for practice to segment the customer base according to the dominant relationship type and to offer each segment a type of robo-advice (hybrid or stand-alone) that matches the respective relationship needs. In addition, and on a more general level, the findings suggest that two common strategic initiatives in services – relationship marketing and service automation – may not always be compatible. Thus, it seems important that managers closely evaluate the strategic ramifications of robo-advisors before introducing such technologies. This implies that, if there is a strategic focus on establishing communal relationships, it is advisable for firms to retain a human element when incorporating robo-advice in the service process.

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RESEARCH ESSAYS

Products and Services in the Digital Age

Dissertation Part II

ESSAY I

Smart Products No More than an Elusive Idea? – Conceptual Review, Synthesis, and Research Directions

Currently under review in the *Journal of Product Innovation Management* (*JPIM*)

SMART PRODUCTS

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NO MORE THAN AN ELUSIVE IDEA?

CONCEPTUAL REVIEW, SYNTHESIS, AND RESEARCH DIRECTIONS

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Abstract

Smart Products have received increasing attention from researchers and practitioners alike. A range of academic fields – including innovation management, information systems, and marketing – contribute to the growing body of knowledge on Smart Products. However, due to their rapid rise and inherently interdisciplinary nature, there is a lack of consensus regarding what defines a Smart Product. Consequently, studies rely on different and partly conflicting conceptualizations which has led to a rather scattered and patchy body of literature with unclear language and conceptual boundaries. This limits comparability across studies and impedes the incorporation of the Smart Product into related concepts such as the IoT. Specifically, scholars use different terms to talk about the same thing (e.g., digitized artefact, intelligent product or smart object) as well as its defining aspects (e.g., situatedness and context-awareness). In such a situation, there is a need to take stock of extant works and develop a common language that supports more cumulative research and, consequently, allows a more structured advancement of the field. To reveal the different understandings of Smart Products, we examined current research through multiple lenses. First, we reviewed existing works on Smart Products across contributing disciplines. This led to an overview of the status quo, that is, an initial set of criteria that are currently applied to characterize “Smart Products”. Based on systematic coding, these criteria were standardized into 19 defining criteria within a hierarchy of 5 levels. Lastly, we pursued a bibliometric analysis to reveal structural patterns underlying the current literature which allowed us to dig deeper into the nature of the diverse understandings of “Smart Products” within and across disciplines. In sum, this study contributes to improving the understanding and conceptual clarity of the “Smart Product”, paves the way for more cumulative research endeavors, and puts forth implications for practice.

Keywords: *Systematic Literature Review, Smart Product, Cumulative Research*

Practitioner Points

- Facing the current flood of terminologies, this article provides a fine-grained framework of reference that is based on a thorough review of research on Smart Products.
- The framework may be used to navigate in the Smart Product world as well as to leverage the firm-internal understanding and dissemination on what a Smart Product is.
- The framework provides starting points from which use-cases can be structured to showcase the far-reaching potential benefits of Smart Products.
- The article covers the complete Smart Product functioning stack which may support organizations in their internal privacy or security risk assessments and helps to detect misalignments with e.g., third-party certification requirements.

Introduction

> "One might wonder whether it would be fruitful, or even possible to theorize or generalize about the nature or impacts of smartness if the same concept purports to describe smart toothbrushes, smart bombs, and smart cities." (Alter 2019 p. 248)
>
> "The identity and capabilities of smart things remain debatable." (Oberländer et al. 2017 p. 2)

In the past decade, the term Smart Product has been buzzing around among politicians, academics, and technology experts alike. In its early days, Smart Products were used mainly for the purpose of philosophizing in technology think tanks and the marketing of cutting-edge technology at trade fairs. However, driven by advancements in technology, Smart Products have today become a tangible reality and in some instances already contributed to the disruption of traditional markets in the dawn of a new era, namely that of the Internet of Things (IoT) and technologized marketing and innovation (Brock 2019; Ng & Wakenshaw 2017).

The term itself has gained inflationary popularity-in-use among practitioners and extant research shows a keen interest in the concept (Shim et al. 2019). For example, recent research has examined Smart Products from the perspective of consumer-object relationships (Novak & Hoffman 2018), general consumer perceptions (Rijsdijk & Hultink 2003; Rijsdijk & Hultink 2009), inhibitors and resistance (Mani & Chouk 2018; Raff & Wentzel 2019; Schweitzer & van den Hende 2016), or the related notion of smart services (Töytäri et al. 2018). A recent guest editorial in the *Journal of Product Innovation Management* (*JPIM*) once more underlines the significant role of IoT and Smart Products as "hot-topics" and cutting-edge fields of research (Bstieler et al. 2018).

However, unfortunately, the current body of knowledge on Smart Products rests on feet of clay: Due to their rapid rise and inherently interdisciplinary nature, there is a lack of consensus regarding what defines a Smart Product. Although there is a large number of thrilling studies, the body of knowledge as a whole is scattered and patchy, and works are often based on ad-hoc conceptualizations and generally characterized by a lack of a common understanding of the term "Smart Product" (Alter 2019; Mayer et al. 2011; Oberländer et al. 2017). Thus, despite its popularity-in-use and compelling calls for research, the Smart Product itself remains an elusive idea rather than a sharply defined *epistemic object* (Alter 2019; Rheinberger 1997).

In this study, we aim to overcome this limitation by dividing it into two sub-problems. First, there is no consensus about the definition and defining criteria of the term "Smart Product". An early definition for the term Smart Product stems from Allmendinger & Lombreglia (2005) who stress that a product gets smart via built-in intelligence through awareness and connectivity. Maass & Varshney (2008) defined Smart Products more extensively via six characteristics: situatedness, personalization, adaptiveness, proactivity, business awareness, and network capability. Porter & Heppelmann (2015) emphasize the connectivity of "smart, connected products" and define three core elements: physical components, "smart" components, and connectivity components. A frequently used definition stems from Rijsdijk & Hultink (2009) who define the concept of smartness as a combination of the dimensions autonomy, adaptability, reactivity, multifunctionality, ability to cooperate, humanlike interaction, and personality, and the scope to which a product possesses one or more of these dimensions. While some works from the fields of information systems (IS), marketing and innovation management relies on or at least refers to this definition for their work with Smart Products (Herterich & Mikusz 2016; Kuijken, Gemser & Wijnberg 2017; Schweitzer & van den Hende 2016; Valencia et al. 2015), other researchers use different definitions or defining criteria when doing research in the field (e.g., Mayer et al. 2011; Meyer, Främling & Holmström 2009; Wangenheim, Wünderlich & Schumann 2017) or come up with their own ad-hoc conceptualizations (e.g., Whitmore, Agarwal & Da Xu 2015). Thus, the need for a common definition represents the first part of the problem we seek to address with this work.

Second, since its inception scholars have established a variety of terms that are used more or less synonymously in place of "Smart Product". To name but a few: Allmendinger and Lombreglia (2005) discuss "smart services" that are bundled with physical products, while Kortuem et al. (2010), Novak & Hoffman (2018) and López et al. (2011) refer to "smart objects". Touzani et al. (2018) discuss "connected objects" and Ng & Wakenshaw (2017) introduce the term "internet-connected constituents". In turn, Herterich & Mikusz (2016) suggest the term "digitized artefact", whilst Miorandi et al. (2012) prefer the term "smart thing" and, lastly, Meyer, Främling & Holmström (2009) use the term "intelligent product". There are even studies using a variety of these terms within the same work without clearly differentiating one from another (e.g., Mani & Chouk 2017; Porter & Heppelmann 2014). Problematically, very few authors address the existence of different terms explicitly in their work (e.g., Kiritsis 2011). This conceptual ambiguity is compounded by the fact that there are other concepts that exhibit overlaps with the Smart Product but nonetheless need to be clearly distinguished in a conceptual sense (Holler, Uebernickel & Brenner 2016). Prominent examples are “ubiquitous computing”, “ambient intelligence”, and above all the ”Internet of Things” (Oberländer et al. 2017).

The fact that there is neither a consensus definition nor a consistent term for the concept as such indicates that research on Smart Products may lack a cumulative knowledge advancement. Such multifaceted and sometimes conflicting views of concepts are not uncommon as can be seen in business model research (Foss & Saebi 2017). However, since management science is a cumulative venture, the lack of a basic common understanding and a precise language pose a severe threat to the development of a cumulative body of knowledge, impede comparability of empirical findings as well as aggravate the link to other concepts (Astley 1985; Keen 1980; vom Brocke et al. 2009). Consequently, an overarching framework or consensus definition may help to organize and baseline present and forthcoming research (Peery 1972). Because unless researchers build on each other's work, a research field can never emerge, no matter how good individual fragments may be (Keen 1980). In addition, Klein & Hirschheim (2003) stress the problem of communication deficits between researchers from the field of IS and reference disciplines, while Bstieler et al. (2018) and Mani & Chouk (2018) call for cross-disciplinary research particularly in the field of Smart Products and the IoT. Given the inherently interdisciplinary nature of the field (e.g., Mikusz 2018; Ng & Wakenshaw 2017), this argument is particularly relevant for Smart Product research. Unless researchers in the field of innovation and related fields like IS and marketing find a common terminological basis and share a specified understanding about Smart Products, an integrated body of knowledge may be slow to emerge (Alter 2018; Klein & Hirschheim 2003).

Taken together, the academic literature relevant to Smart Products comprises a large number of disconnected research efforts from different disciplines, often relying on different definitions and understandings of the underlying concept. It is against this backdrop that we believe that the debate of Smart Products and related topics that was repeatedly called for in *JPIM* (e.g., Barczak 2016; Bstieler et al. 2018) can only be fertile if there are clarity and consensus about the *epistemic thing*, namely the Smart Product itself (Rheinberger 1997). In light of such a young, fast-moving and rapidly evolving field, it might be audacious but important to step back and first address this issue in order to create a basis for future research initiatives in the field (Bstieler et al. 2018). Thus, in service of this issue, the objective of this work is to shed light on current research and the conceptualizations for Smart Products in order to reveal the definitions and descriptive elements that are currently applied. Moreover, based on a synthesis and coding of these criteria, we aim to derive a standardized and comparable set of defining criteria for Smart Products. Lastly, we attempt to carve out relevant issues and tensions in the current literature to guide future research and practice. To do so, our research efforts are guided by the following three research questions:

RQ1. What is the content of the current academic body of literature investigating Smart Products? [Review]

RQ2. How can extant research be synthesized towards a set of standardized defining criteria for Smart Products? [Synthesis]

RQ3. What are the limitations of current research and promising avenues for future investigation? [Directions]

With these questions in mind, the following two-part study was undertaken: First, as a crucial step towards delineating the applied definitions and descriptive elements for Smart Products, a cross-disciplinary systematic literature review (SLR) was conducted (Barczak 2017; Webster & Watson 2002). Similar to other novel domains that have benefitted from SLRs such as business models (e.g., Li 2018), business model innovation (e.g., Foss & Saebi 2017) or design thinking (e.g., Micheli et al. 2018), a rigorous SLR for Smart Products may help to grasp the whole of this multifaceted and interdisciplinary concept. Second, we performed a supplementary bibliometric analysis in order to provide quantitative insights and to reveal structural patterns in the evolution of the Smart Product literature (Palmatier, Houston & Hulland 2018). Combining the results from these two steps allowed us to dig deeper into the nature of disagreements or agreements of the different understandings of “Smart Products”. Based on the analysis and synthesis of our findings this study makes three basic contributions to both theory and practice. (1) A scattered and patchy body of knowledge is systematically condensed and synthesized into a set of 19 defining criteria for Smart

Products. (2) Based on these criteria, we propose a generative framework for Smart Products consisting of 5 hierarchical levels and a standardized terminology that may support dialogue about the phenomena and serve as an entry point for future research, leaving enough margin to allow further refinement if needed (Rheinberger 1997). (3) Finally, this review provides an interdisciplinary state-of-the-art snapshot of current research on Smart Products, which allows us to spot current discrepancies and blind spots, but also to highlight promising opportunities for future research and practice (Barczak 2017; Bstieler et al. 2018; Palmatier, Houston & Hulland 2018). In addition, from a methodological perspective, we contribute by developing a conformity score that allows representing the diverging understandings about concepts in a quantitative manner and on the basis of a set of standardized criteria.

The remainder of this paper is organized as follows. In the next section, we rigorously describe the steps pursued in our SLR as well as provide descriptive insights into our final literature sample. Subsequently, we present the synthesized results from our SLR that are based on our in-depth content analysis and data coding. This is followed by the supplementary bibliometric analysis of our findings. Last, we carve out implications for research and practice.

Systematic Review of the Smart Product Literature [Review]

An SLR consists of the quest for relevant literature on a particular topic and involves the following three broad steps: data collection, analysis, and synthesis (Tranfield, Denyer & Smart 2003). Our SLR was guided by the widely accepted instructions given by Tranfield, Denyer & Smart (2003), vom Brocke et al. (2009) and Webster & Watson (2002). In specific, we pursued a concept-centric literature review (Webster & Watson 2002), which is best suited when attempting “to tackle an emerging issue that would benefit from the development of new theoretical foundations“ (Paré et al. 2015 p. 188). An SLR needs to be systematic in terms of the methodological approach, explicit through a clear explanation and documentation of the steps pursued, comprehensive in its scope, and reproducible by others following the same review steps (Templier, Paré & Rowe 2018; Webster & Watson 2002). In order to fulfil these requirements, the following multistep approach to detect and select sources that discuss the concept of Smart Products was applied: (i) database search across different disciplines, (ii) title and abstract screening, (iii) content evaluation and quality appraisal, and (iv) backward and forward search. This process left us with a final sample of 37 articles for in-depth content analysis (Bryman 2016). Figure 1 provides a comprehensive overview of the literature search and selection process.

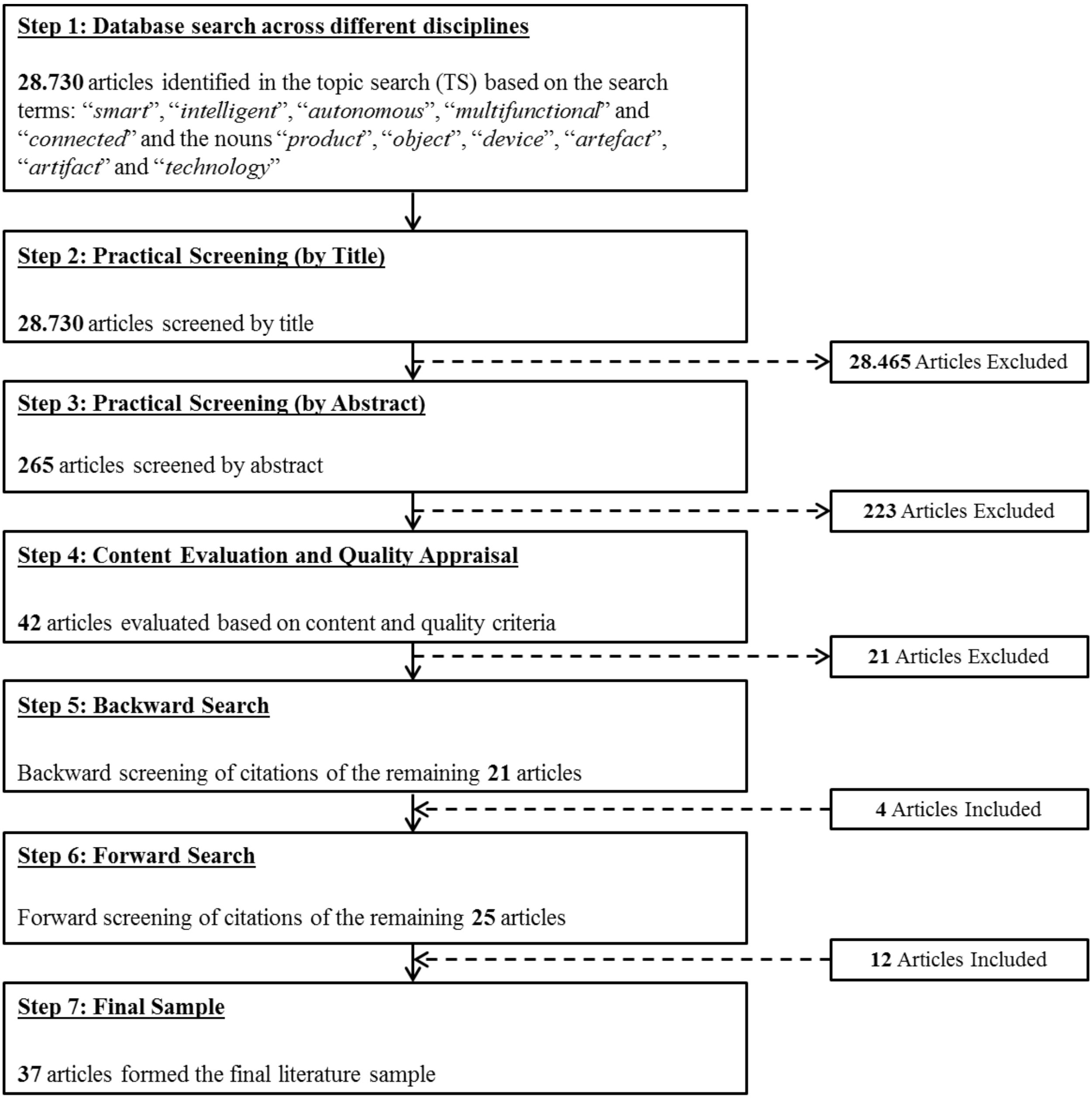

Figure 1. Flow chart of the literature search process

Database Search across Different Disciplines

The Web of Science database (WoS) was considered to provide an adequate and comprehensive collection of relevant academic literature and was therefore used for our literature search. The overall structure of the literature search and filter process was broad and inclusive in nature, aiming at bringing together different streams of literature in order to comprehensively collect all articles that may contain Smart Product-related research (Paré et al. 2015). As the field of Smart Products is inherently interdisciplinary, the literature search was broad across all document types and business domains, including – but not limited to – marketing, innovation, and IS (Ng & Wakenshaw 2017; Webster & Watson 2002). For the determination of the time span for the primary literature research process we initially checked current literature with a focus on Smart Products and related topics, such as ubiquitous and pervasive computing, smart technologies, and the IoT. A review of the respective references revealed that the period between 1998 and 2018 appears to be a reasonable time frame.

The final search string for the identification of the corpus of relevant literature was developed through an iterative process of reviewing extant literature and a lively exchange with experts from academia and practice. First, top-tier articles in the context of ubiquitous and pervasive computing, smart technologies, and the IoT were scanned to shed light on the potential keywords to be included in our search string. Second, discussions with experts from the field brought about further input leading us to a varied thesaurus of keywords evolving around the adjectives “smart”, “intelligent”, “autonomous”, “multifunctional” and “connected” and the nouns “product”, “object”, “device”, “artefact”, “artifact” and “technology”. Using these terms as search terms in our final search string resulted in 28.730 papers.

Practical Screening

In a first step, we pursued a manual cursory analysis of the articles based on title and abstract. This approach was inspired by recent reviews from the field that had faced equally large samples in their first search round (e.g., Micheli et al. 2018; Vries, Bekkers & Tummers 2015). This process left us with 264 articles. Afterwards, we read the abstracts of the 264 remaining papers thoroughly and, in the case of a promising abstract, also portions of the text to further narrow down the selection. In this process, the thematic positioning of each paper was pivotal for the evaluation: papers that focused predominantly on technical aspects tended to be excluded if they did not cover Smart Products in their entirety. Since the aim of this work is a review of existing definitions, especially papers that attribute general properties to Smart Products were chosen. Work that was limited to a specific product or product group, without drawing generalizable conclusions about Smart Products, was also excluded.

Content Evaluation and Quality Appraisal

Next, we read the 42 remaining papers and evaluated them in terms of their content. Following this, we developed a coding scheme that contained detailed descriptive data, content summaries as well as our personal comments. In addition to the content, several quality criteria were considered for the inclusion in the final sample, such as the rating of the source, the journal, or the conference proceeding in which the paper was published. We used the *Financial Times* ranking (*FT50*) and the German *Verband der Hochschullehrer für Betriebswirtschaft* (*VHB*) ranking for the evaluation of sources. Moreover, we explicitly decided to include conference papers (henceforth article or paper for short) in our sample, since in an initial literature scan we found a number of conference articles that became very influential to this fast-moving and dynamic field (e.g., Wong et al. 2002). Moreover, we expected a lot of recent research to be presented first at conferences before eventually passing through the longer review cycles of journals. For the conference papers, special attention was paid to considering – but not limited to – those that were presented at high-quality conferences such as for example the Proceedings of the *Hawaii International Conference on System Sciences* (*HICSS*), *International Conference on Information Systems* (*ICIS*) or the *IFIP WG 8.6 pre-ECIS International Working Conference "Smart Working, Living and Organising" on Transfer and Diffusion of IT* (*TDIT 2018*). Based on the process described above, 21 papers were selected for the initial sample of papers.

Backward and Forward Search

Conducting a backward and forward search via cross-references is particularly important for concept-centric literature reviews as it increases the completeness and reliability of the resulting literature list (Tranfield, Denyer & Smart 2003; vom Brocke et al. 2009). This step resulted in the identification of 16 additional articles, bringing the final literature list for in-depth analysis and data extraction to 37 papers. All papers from the final literature sample can be found in Appendix A and are denoted by an asterisk in the reference list.

Data Analysis and Sample Description

The data analysis started with a descriptive analysis in which each paper was read and summarized; thereafter, a coding scheme was developed and for each paper, the key defining criteria of Smart Products were extracted and listed. As previously described, these criteria were later coded into the basic defining criteria of Smart Products.

The chronological publication distribution of the reviewed literature is depicted in Figure 2. It shows the increasing body of knowledge after 2015, mirroring the emerging nature and growing relevance of the research field. 22% (8 of 37) of the articles from our final literature sample originate from the years 2002 until 2009. 78% (29 of 37) of the articles originate from the years 2010 until 2019. As can be seen, publications currently peak since the rise of mainstream adoption of Smart Products such as the Amazon Echo (Mallat, Tuunainen & Wittkowski 2017). 28 articles from our sample are published in high-quality peer-reviewed journals (except *Harvard Business Review* (*HBR*) as a practitioner-oriented outlet) including the *Journal of Product Innovation Management* (*JPIM*), *Journal of Consumer Research* (*JCR*), *Journal of the Academy of Marketing Science* (*JAMS*), *Information & Management* (*IM*), *International Journal of Research in Marketing* (*IJRM*), *IEEE Computer, Information System Frontiers* (*ISF*), *Electronic Markets* (*Electron. Mark*.), *Psychology & Marketing* (*P&M*), or the *International Journal of Operations & Production Management* (*IJOPM*). From a journal perspective, *JPIM* had the highest appearance in our sample (Bstieler et al. 2018; Mani & Chouk 2018; Rijsdijk & Hultink 2009; Rijsdijk & Hultink 2003) with four appearances, followed by *HBR* (Allmendinger & Lombreglia 2005; Porter & Heppelmann 2015; Porter & Heppelmann 2014) with three appearances (Appendix B). Nine sources appeared in conference proceedings from the fields of IS and innovation management such as the *WI*, *HICSS* and *ICIS*. From a conference perspective, *ICIS* Proceedings had the highest appearance in our sample, contributing with 2 articles (Herterich & Mikusz 2016; Püschel, Schlott & Röglinger 2016). The final sample includes 9 empirical and 28 theoretical contributions (see Appendix A). Table 1 shows that the majority of the articles from our sample (18) are based on ad-hoc conceptualizations or own definitions for Smart Products, 12 articles use a definition that is based on a combination of descriptive elements from previously established definitions, and 7 articles base their articles on previously established ones which is a first indication of the fields non-cumulative nature. Additionally, a brief analysis via the WoS citation analysis tool provided support for the inherently interdisciplinary nature of current Smart Product literature (as of January 2019). As an example, the influential Smart Product articles by Rijsdijk & Hultink (2009) and Porter & Heppelmann (2014) from the innovation and marketing field received 14.4% and 10.3% of their overall citations from the IS domain.

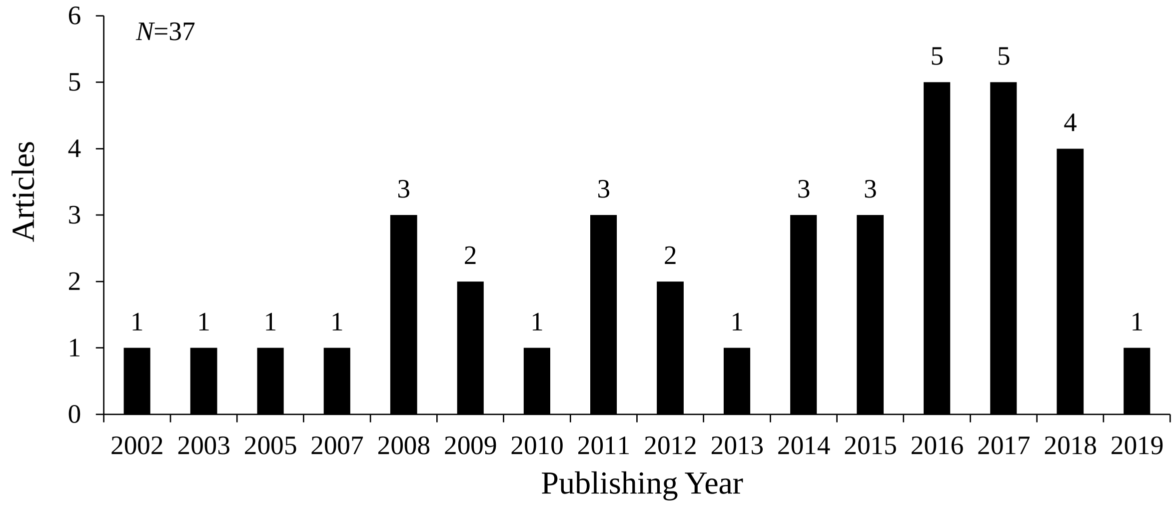

Figure 2. Year of publication of the articles in the final literature sample

Table 1. Literature sample: research domain, research perspective and respective definition approach

Article	Research Domain	Research Perspective	Ad-hoc Conceptualization	Based on an established Definition suggested in a Previous Article (Authors)		Based on Combined Definitions
Wong, McFarlane, Zaharudin, Agarwal (2002)	IS	Organizational (O)	**x**			
Rijsdijk and Hultink (2003)	Inno & Mar	Consumer/User (CU)				**x**
Allmendinger and Lombreglia (2005)	Inno & Mar	O	**x**			
Rijsdijk,Hultink& Diamantopolus (2007)	Inno & Mar	CU/P	**x**			
Valckenaers, and Van Brussel (2008)	Inno & Mar	Product (P)	**x**			
Maass and Varshney (2008)	IS	P		**x**	(Maass and Jantzen, 2007)	
Mühlhäuser (2008)	IS	P	**x**			
Meyer, Framling, Holmström (2009)	IS	P				**x**
Rijsdijk and Hultink (2009)	Inno & Mar	CU		**x**	(Rijsdijk and Hultink, 2002, definition equals Rijsdijk and Hultink, 2009)	
Kortuem, Kawsar, Fitton, Sundramoorthy (2010)	IS	P	**x**			
Kiritsis (2011)		P/O				**x**
Mayer, Volland, Thiesse, Fleisch (2011)	IS	CU				**x**
López, Ranasinghe, Patkai, McFarlane (2011)	IS	P	**x**			
López, Ranasinghe, Harrison, McFarlane (2012)	IS	P	**x**			
Miorandi, Sicari, De Pellegrini, Chlamtac (2012)	IS	P/O	**x**			
Gutierrez, Garbajosa, Diaz, Yagüe (2013)	IS	P	**x**			
Pérez Hernández, Reiff-Marganiec (2014)	IS	P/O		**x**	(Wong, McFarlane, Zaharudin, and Agarwal, 2002)	
Porter and Heppelmann (2014)	Inno & Mar	O/P/CU	**x**			
Meyer, Buijs, Szirbik, Wortmann (2014)	Inno & Mar	P/O				**x**
Porter and Heppelmann (2015)	Inno & Mar	O		**x**	(Porter and Heppelmann, 2014)	
Dorsemaine, Gaulier, Wary, Kheir (2015)	IS	P	**x**			
Whitmore, Agarwal, Xu (2015)	IS	P/O	**x**			
Baird and Riggins (2016)	IS	O/P/CU	**x**			
Mani and Chouk (2017)	Inno & Mar	CU				**x**
Herterich and Mikusz (2016)	IS	P	**x**			
Schweitzer and Van den Hende (2016)	Inno & Mar	CU				**x**
Holler, Uebernickel, Brenner (2016)	IS	O				**x**
Püschel, Schlott, Röglinger (2016)	IS	P				**x**
Ng and Wakenshaw (2017)	Inno & Mar	O/P/CU				**x**
Gonzalez Garcia, Meana-Llorian, Pelayo G-Bustelo, Cueva Lovelle (2017)	IS	P				**x**
Dawid, Decker, Hermann, Jahnke (2017)	Inno & Mar	O/P/CU	**x**			
Touziani et al. (2018)	IS	CU	**x**			
Hoffman and Novak (2017)	Inno & Mar	CU				**x**
Bstieler et al. (2018)	Inno & Mar	O/P/CU	**x**			
Mani and Chouk (2018)	Inno & Mar	CU		**x**	(Hoffman & Novak, 2015)	
Novak and Hoffman (2018)	Inno & Mar	CU		**x**	(Rijsdijk and Hultink, 2009)	
Raff and Wentzel (2019)	IS	CU		**x**	(Rijsdijk and Hultink, 2009)	
Sum			18	7		12

Basic Defining Criteria and Smart Product Hierarchy [Synthesis]

The in-depth content review of the selected articles revealed the different defining characteristics that form the current conceptualizations of Smart Products (Bryman 2016). In most of the articles, the underlying understanding of what defines a Smart Product could be found in either the introduction section or the conceptual background section. In general, there exist very few definitions for Smart Products that have found cumulative application in our sample through being re-cited (Table 1). One was introduced by Rijsdijk, Hultink & Diamantopoulos (2007) in *JAMS* (slightly adapted later on in *JPIM* by Rijsdijk & Hultink (2009)). According to the authors, a Smart Product is characterized by the seven dimensions: *autonomy*, *adaptability*, *reactivity*, *multifunctionality*, *ability to cooperate*, *humanlike interaction*, and *personality* and "the extent to which it possesses each of these dimensions" (p. 342). Moreover, an alternative cited definition that was proposed by Porter & Heppelmann (2014) in *HBR* characterizes Smart Products as a combination of the three core elements *physical components*, *smart components*, and *connectivity components*. Moreover, the authors mention that Smart Products are enabled by the information technology (IT) that is embedded in physical objects, such as sensors, processors, software implementation, and connectivity modules that allow the storage of captured data in a product cloud. A further re-cited definition comes from Wong et al. (2002) and describes an intelligent product as "one that has part or all of the following five characteristics: 1. Possesses a unique identity, 2. Is capable of communicating effectively with its environment, 3. Can retain or store data about itself, 4. Deploys a language to display its features, production requirements etc., 5. Is capable of participating in or making decisions relevant to its own destiny" (p. 7).

During the analysis of the literature sample, we found more indicators that authors often implicitly list the same defining criteria but name them differently. For example, the "connectivity to other products" and "networking of Smart Products" both describe the Internet-based connection between objects. The same applies to "context-awareness" and "situatedness" which both stand for some sort of real-time context awareness. Thus, if taking a closer look at the diverse Smart Product definitions that are used in current literature, a certain degree of commonality emerges: While a variety of authors have defined Smart Products in slightly different ways and thereby used a range of defining criteria, some of them are synonymous or used more regularly, suggesting a level of concurrence. Thus, in order to be able to systematically compare different definitions, we initially had to standardize them. Thus, we first dissected the applied definitions into their constituting elements and performed subsequent inductive data coding by grouping sets of related codes into basic defining criteria (Boyatzis 1998). Following this approach, an initial set of 60 defining criteria were grouped into 19 basic defining criteria of Smart Products within 5 Smart Product levels (see Table 2)[1]. For example, we subsumed the descriptive properties "communicate with other equipment", "communicate with other objects" or "communication capabilities" under "Communication and Information Exchange". Thus, the resulting basic defining criterion encompasses all communication and information exchange-related aspects of Smart Products. The data coding was pursued by two independent scholars from the fields of marketing and innovation leading to a moderate interrater-agreement after the first round of coding (*Cohen's kappa* = 0.61) (Cohen 1960). In a next step, initially diverging views were discussed and aligned with extant theory in further rounds of refinement towards the final coding of 19 basic defining criteria within the 5 hierarchical Smart Product levels *(1) Hardware and Data Management*; *(2) IoT Capabilities*; *(3) Sensing, Reacting and Anticipation*; *(4) Independent Action*; and *(5) Anthropomorphism* (see Figure 3).

Overall, the suggested hierarchy depicts a constitutive architecture of Smart Products following the logic of a needs hierarchy. In this hierarchy, each level represents a foundation that needs to be satisfied to a certain extent in order to allow a product to evolve from a basic IT-enabled product (e.g., a digital camera) into an IoT-enabled product and ultimately into a Smart Product enabled by artificial intelligence (AI). Level 3 from our hierarchy describes a transitional level that allows distinguishing a simple level 2 IoT Product (e.g., Amazon Dash Button) from more sophisticated IoT Products (e.g., Amazon Echo or Sonos Speaker) that may further evolve into higher levels via added AI and machine learning capabilities such as the Nest Learning Thermostat.

[1] Please note that we only included explicitly mentioned defining criteria in our data coding although it may have occurred that authors implicitly spoke about further criteria. Thus, explicit criteria reflect properties that authors have particularly been written out for the definition or characterization of Smart Products, whereas implicit criteria are properties that are additionally attributed to a Smart Product in the course of the research paper.

Our standardization of the criteria improves the comparability of the papers and definitions along the criteria and helps to reduce distortions based on individual wording and the use of synonyms. Table 2 and Appendix C provide the full picture of the defining criteria, their respective underlying codes from the papers, example quotes as well as the featuring authors.

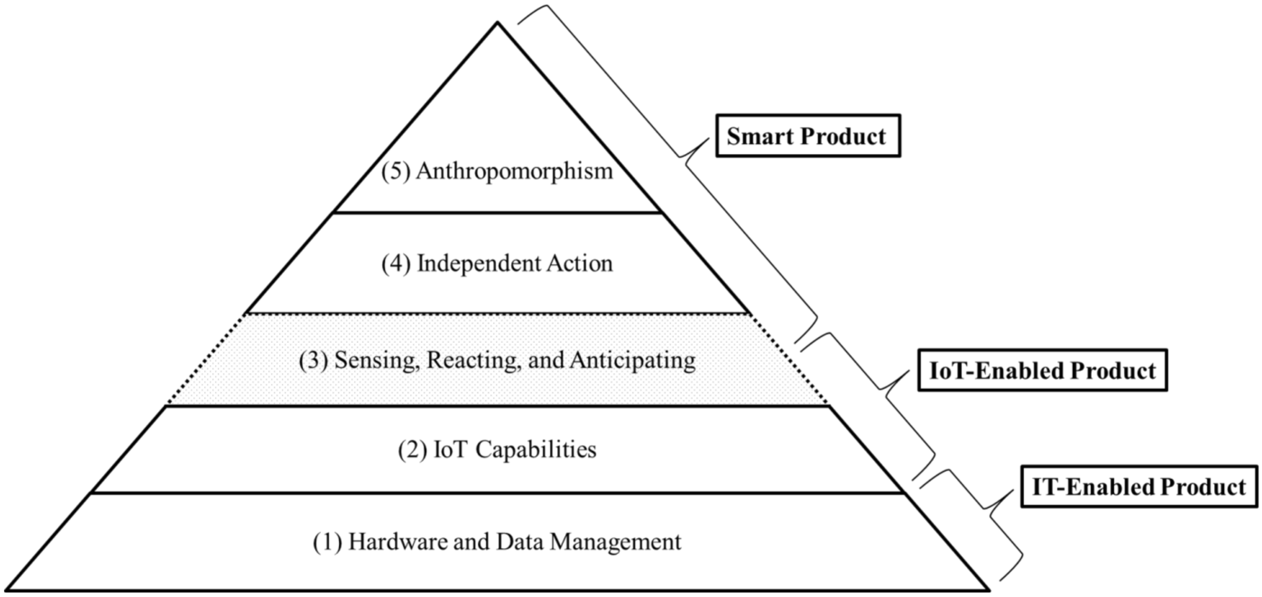

Figure 3. Derived Smart Product hierarchy

Table 2. Basic defining criteria, codes and frequency of occurrence

Basic Defining Criteria	Frequency	Code (wording as applied in current literature)*	Example Quote
(1) Hardware and Data Management			
IT Equipped Physical Object	18	Physical objects, equipped with sensors and actuators / Embedded operation system equipped with intelligence-generating technologies / Sensors and actuators embedded into everyday objects and devices products that contain IT / Physical and information-based representation of a product object equipped with IT / Physical components and smart components / Digital and physical maternality / Physical embodiment / Traditional industrial products and machines get empowered by digital technologies / Everyday objects (…) equipped with (…) capabilities / Consumer objects	"Sensors that collect data, and actuators that transmit that data, are being increasingly incorporated in all manner of consumer objects commonly found in and around the home, worn on or in the body, and used in consumption activities involving shopping, entertainment, transportation, wellness, and the like" (Hoffman and Novak, 2017 p. 1178).
Data Capturing and Tracking	11	Gather data / Collect data / Retain data / Data it collects Condition / State capturing / Profiling and behaviour tracking /	"An intelligent product can be defined as a physical and information-based representation of a product, which can retain or store data about itself (..)" (Meyer et al., 2014 p. 428).
Data Storage (Hardware or Cloud)	13	Retention / Cloud storage / Storage / Store data / Data storage Store measurements / Store information / Memory	"An intelligent product (…) can retain or store data about itself" (Wong et al., 2002 p. 2).
Data Processing and Analysis	17	Information processing / Data analysis /Diagnostic / Use the data / Processing / Transport / Process environment data /Aggregate data /Analyze data / Data processing / Compute complex computations / These products can process and analyze user data / Transmit the data	"We see an intelligent product as a product system which contains (…) data processing, (…)" (Kiritsis, 2011 p. 480).
Data Provision and Transmission	12	Provision of identification and product information / Access to the generated data by users or other systems / Are able to make their identification, sensor measurements, and other attributes available to external entities / Semantic self-description /	"(…) are able to make their identification, sensor measurements, and other attributes available to external entities such as other objects or systems" (Lopez et al., 2011 p. 295).

* *Codes are only provided if different terms as the derived final basic defining criterion were employed*

Table 2. *(Continued)*

		(2) IoT Capabilities	
Unique Identification	9	Unique identity / Uniquely identifiable / Human-readable (object description) / The address is a machine-readable string / Can be identified throughout its life / Identify themselves / Make their identification / Existence of a unique and immutable identity / Unique identifier	"Smart Objects are those objects that possess a unique identity, (...)" (Lopez et al., 2011 p. 295).
Networking and Connectivity	19	Part of an infrastructure / Interact with the environment and other objects / Work together as assemblages / Communication networks / Network connectivity / Network connection to other devices / One-to-One, one-to-many, Many-to-many connectivity / Connected constituents / Self-organized embedding into different (smart) environments / Interoperate with other products /	"(…) a system of uniquely identifiable and connected constituents (…)" (Ng and Wakenshaw, 2017 p. 6).
Communication and Information Exchange	21	Interfaces to exchange information with their environment / Communicate with other equipment / Communicate with other objects / Wireless communication technology / Can communicate / Communicate with each other / Report its location, condition, and/or state / Able to communicate / Interchange information / Communicate with other products / Communication functionalities / Communication capabilities	"Smart products show at least one of these characteristics. First, products become able to communicate with other products" (Rijsdijk and Hultink, 2003 p. 205).
Interaction and Cooperation	18	Ability to cooperate / Interact with the environment and other objects / Interact with each other / Interaction / Operate and interact with other devices / Participating / Interaction with and along smart things / Interact with users / Ongoing interaction	"Smart products include those that can perform one or more of these tasks: collect and transmit user data, independently interact with users" (Bstieler et al., 2018 p. 305).
		(3) Sensing, Reacting, and Anticipating	
Sensing	18	Sensors / Sensing / Miniaturized Sensors / Able to sense / Status applications	"Smart components comprise the sensors, (…)" (Porter and Heppelmann, 2014 p. 5).
Real-Time Context Awareness	5	Situatedness / Interaction by means of context-awareness / Use information about the environment in which they run / Business awareness	"In compliance with the first requirement, the first dimension is "Situatedness", which refers to the recognition of situational and community contexts" (Mass and Varsheny, 2008 p. 213).

Table 2. *(Continued)*

Reactivity and Adaptability	10	Adaptability / Alter its location, condition, and/or state / Adapt their actions to different situations / Independently improve their performance / Reactivity	"The ability of a product to react to changes in its environment in a stimulus/response manner" (Rijsdijk, Hultink, and Diamantopolus 2007 p. 342).
Proactivity	4	Proactive behaviour / Proactivity	"A Smart Product is an entity (…) providing improved simplicity (…) by means of (…) proactive behavior, (…)" (Mühlhäuser, 2008 p. 6).
Multifunctionality	4	Multifunctionality	"(…) defined this construct as consisting of seven dimensions: (…), multifunctionality, (…)" (Rijsdijk and Hultink, 2009 p. 25).
Customization	1	Personalization	"'Personalization' in terms of customizing of products in accordance to consumer's needs and affects (…)" (Mass and Varsheny, 2008 p. 213).
		(4) Independent Action	
Autonomy and Self-Management	20	Act in an intelligent way and independently / Activate an action / Activate actions / Autonomy / Work fully autonomously / (Making decisions) relevant to its own destiny / Trigger actions / Self-organized / (Make decisions about) themselves / What can be done for them (consumers)	"(…) defined this construct (smartness) as consisting of seven dimensions: autonomy, (…)" (Rijsdijk and Hultink, 2009 p. 25).
Reasoning and Decision-Making	11	Reasoning / Can make decisions about themselves and their interactions / Making decisions / Participating in decisions /	"(Smart Objects) can make decisions about themselves and their interactions with external entities" (Lopez et al., 2011 p. 295).
Actuation	6	Actuators / Influence condition or state of environment / Alter its location, condition, and/or state / Actuation / Miniaturized actuators	"(...) smart products have: (…) 'actuators' that activate an action (…)" (Mani and Chouk, 2017 p.4).
		(5) Anthropomorphism	
Anthropomorphism	3	Humanlike interaction / Personality / (human-centric anthropomorphism)	"The degree to which the product communicates and interacts with the user in a natural, human way" (Rijsdijk, Hultink, and Diamantopolus 2007 p. 343).

The following sections will be organized along the derived Smart Product levels and provide short descriptions of the basic defining criteria as embedded in current research.

First Level: Hardware and Data Management

The first level, "Hardware and Data Management" refers to foundational elements of any Smart Product, i.e. the availability of physical devices that support basic data processing functionalities.

IT Equipped Physical Object. Most authors (18 appearances) explicitly define Smart Products as "products that contain information technology" (e.g., Schweitzer & van den Hende 2016, p. 830). Whilst this is tautologic thus not surprising per se, this aspect represents one of the most widely agreed on least common denominators for describing an intelligent product. Hoffman & Novak (2017) specify this aspect as "sensors that collect data, and actuators that transmit that data, are being increasingly incorporated in all manner of consumer objects commonly found in and around the home, worn on or in the body, and used in consumption activities involving shopping, entertainment, transportation, wellness, and the like" (p. 1178). Porter & Heppelmann (2015) stress the opportunities for innovation via the more far-reaching functionalities of Smart Products (as compared to traditional products) enabled by embedded IT.

Data Capturing and Tracking. Another common descriptive characteristic of Smart Products is data capturing and tracking (11) (e.g., Allmendinger & Lombreglia 2005; Dawid et al. 2017; Hoffman & Novak 2017). The ability to register data is an important prerequisite for data analysis and the creation of a quantified self through reporting delivery (Touzani et al. 2018). However, the ability to register data not only benefits the user but also allows firms to improve product features on the software level or to estimate a need for maintenance even after the product launch (Dawid et al. 2017; Meyer, Främling & Holmström 2009). In addition, the captured data may feed into the product development process and thus bear great potential for new products (Bstieler et al. 2018; Dawid et al. 2017; Holler, Uebernickel & Brenner 2016).

Data Storage (Hardware or Cloud). In addition to their data capturing capabilities, intelligent products are characterized by their ability to retain or store data (13) (López et al. 2012; Meyer et al. 2014; Meyer, Främling & Holmström 2009). The storage of the data can either reside in the product itself or in an external data cloud (Porter & Heppelmann 2015).

Data Processing and Analysis. Smart Products are usually able to perform sophisticated data analysis (17) where the collected data is used as input to algorithms that control how a product operates (Baird & Riggins 2016). In addition, the data collected can provide firms with insights regarding product usage, customer preferences, and customer satisfaction (Porter & Heppelmann 2014). These patterns extend the possibilities for companies far beyond the point of sale, as the company receives important insights about the value-creating aspects of its product (Dawid et al. 2017). This, in turn, allows for better product design and positioning as well as finer-grained customer segmentation (Dawid et al. 2017; Porter & Heppelmann 2014).

Data Provision and Transmission. A Smart Product possesses the ability to "report its location, condition, and/or state" (12) (Baird & Riggins 2016 p. 1793). This way of displaying information to external entities is often mentioned as a key criterion for Smart Products (e.g., López et al. 2012; Meyer, Främling & Holmström 2009; Touzani et al. 2018). Moreover, it is the key driver of lifelogging and the emergence of a quantified self (Touzani et al. 2018).

Second Level: IoT Capabilities

On the second level of the proposed hierarchy, "IoT Capabilities" describe a product's technical ability to connect and engage within a larger Internet of Things.

Unique Identification. There is a broad agreement (9) that a Smart Product is characterized through a specific digital identity that allows for unique identification via automatic identification technologies (e.g., active or passive RFID tags) (e.g., López et al. 2012; Meyer, Främling & Holmström 2009; Miorandi et al. 2012; Ng & Wakenshaw 2017). Such a unique identification allows automatically and uniquely identifying, locating, and tracking smart objects throughout the course of their lives (González García et al. 2017; López et al. 2012; Wong et al. 2002). Overall, Ng & Wakenshaw (2017) highlight the aspect of internet-connected constituents being uniquely identifiable as a key driver of the IoT.

Networking and Connectivity. The frequently used (19) defining aspect of "Networking and Connectivity" describes the fact that a Smart Product is connected within a larger internet of things which in a next step allows it to communicate, to cooperate, to interact and to support remote control. Thereby the respective communication, cooperation or interaction partners may vary and include other intelligent products (Kiritsis 2011), the user (Mühlhäuser, Ferscha & Aitenbichler 2008) or other systems in the environment (Meyer, Främling & Holmström 2009). Inspired by Descartes' famous *Cogito ergo sum*, Touzani et al. (2018) introduced *Connecto ergo sum*, which emphasizes the central role of connectedness in the context of intelligent products and the resulting possibility of expressing one's extended self. In addition, from a practitioner perspective, Touzani et al. (2018) urge that "the promising possibilities of connected objects make it important for managers to improve their understanding of the transformations that affect behaviors and the opportunities that these can offer" (p. 472).

Communication and Information Exchange. A wide range of authors described Smart Products as engaging in "communication and information exchange" through connectedness (Schweitzer & van den Hende 2016). This defining aspect has received the largest application in our literature sample (21). Broadly speaking, this aspect refers to the products' ability to exchange ideas and pieces of information with other units such as objects or firms (e.g., Ng & Wakenshaw 2017; Porter & Heppelmann 2015; Rijsdijk & Hultink 2003; Touzani et al. 2018) . Communication and information exchange represents the driving force to the emergence of different types of consumer-object assemblages as well as the IoT at large (Hoffman & Novak 2017; Ng & Wakenshaw 2017). An example illustrating the mix of different types of communication abilities of Smart Products is the *consumer-centric communication* in the use of Amazon Echo for home-to-home "drop-in" calls combined with *nonconsumer-centric object-to-object communication* in the necessary connection between two Amazon Echo devices (Hoffman & Novak 2017). Technically, communication may be realized via the whole array of available network technologies including internet technologies, technologies in sensor networks, and near field communication (NFC) such as via high-frequency RFID tags (López et al. 2011; Mayer et al. 2011; Püschel, Schlott & Röglinger 2016; Whitmore, Agarwal & Da Xu 2015).

Interaction and Cooperation. A wide range of researchers (18) in our sample have highlighted the importance of "Interaction and Cooperation" as a key descriptive feature for Smart Products (Hoffman & Novak 2017; López et al. 2012; Novak &

Hoffman 2018; Püschel, Schlott & Röglinger 2016). Smart Products have unique capabilities that allow them to interact with consumers as well as with other smart devices (Novak & Hoffman 2018). For example, people can interact with Amazon Echo's "Alexa" via its ability to process voice command and its large array of "skills" towards the end of a co-created outcome (Novak & Hoffman 2018). These interaction options, in turn, provide an important prerequisite for the emergence of consumer-object relationships (Novak & Hoffman 2018). Moreover, they also represent a crucial driver for object-to-object assemblages such as the IoT (Hoffman & Novak 2017; Ng & Wakenshaw 2017). Thus, broadly speaking, the capability to interact allows Smart Products to "work together as assemblages through a process of ongoing interaction" (Hoffman & Novak 2017 p. 1179). Overall, compared to the aspect of "Communication and Information Exchange", which describes the mere exchange of pieces of information, the aspect "Interaction and Cooperation" describes the joint collaboration between Smart Products and the user towards a common goal. In addition, Novak and Hoffman (2018) add an interesting new facet to these interactions, emphasizing that Smart Products themselves may now have their own experiences and express their own roles (agentic/communal). Thus, when analyzing how the product and user cooperate, also the underlying roles and experiences of the products have to be considered.

Third Level: Sensing, Reacting, and Anticipating

The third level, "Sensing, Reacting, and Anticipating" consists of the functional product characteristics that support active awareness or anticipation of the user and the environment as well as corresponding reactions.

Sensing. Smart Products can be characterized by their sensing capabilities (8) realized via sensor technologies (e.g., contact and motion sensors for Amazon Echo) (e.g., Meyer, Främling & Holmström 2009; Miorandi et al. 2012; Perez Hernandez & Reiff-Marganiec 2014). Broadly defined, sensing deals with the products' technical ability to actively acquire or possess knowledge about the environment or about itself (Allmendinger & Lombreglia 2005; Baird & Riggins 2016; Dawid et al. 2017; Porter & Heppelmann 2015; Püschel, Schlott & Röglinger 2016). Porter and Heppelmann (2015) discuss the application of sensors in the context of smart home devices in order to illustrate their ability to measure moisture, smoke, temperature or motion. Such sensing of the environment and the product's own condition brings about several advantages such as for example gaining important insights into the product's performance and warnings in out-of-condition situations (Meyer et al., 2009; Porter and Heppelmann, 2015). With regard to a Smart Product's sensing capabilities, Püschel, Schlott & Röglinger (2016) conclude that "the more and the richer data a smart thing can collect, the sounder the foundation for higher-level interactions" (p. 8). A good example for products sensing capabilities is the "Cool to Dry" function of the Nest Learning Thermostat, that activates the connected air conditioner or heating system as soon as soon as it senses above normal levels of humidity. Overall, "Sensing" represents an important precondition for "Reactivity and Adaptability" (Baird & Riggins 2016; Mayer et al. 2011; Rijsdijk & Hultink 2003).

Real-Time Context-Awareness. A further revealed defining criterion of Smart Products is "Real-Time Context-Awareness" (5). It describes the fact that a Smart Product is aware of several different aspects of its environment. Awareness includes for example the awareness of the context (Mayer et al. 2011; Mühlhäuser, Ferscha & Aitenbichler 2008), the awareness about themselves (Gutierrez et al. 2013; Mayer et al. 2011) or the awareness of business and legal constraints (Maass & Varshney 2008). Real-time context awareness is consequential to the aspect of "Sensing" and a crucial antecedent to "Reactivity and Adaptability".

Reactivity and Adaptability. A number of authors (10) use the aspect of reactivity and adaptability to describe Smart Products (e.g., Meyer, Främling & Holmström 2009; Rijsdijk, Hultink & Diamantopoulos 2007; Rijsdijk & Hultink 2009). In the current literature, it has often been described that Smart Products can tailor their actions to the environment. This, for example, may include the adaption to the room in which the product is placed or to the person who is using the product (Rijsdijk & Hultink 2009) and his or her preferences (Porter & Heppelmann 2014). Thus, in general, this aspect describes a product's ability to observe and take action based on the observation (Rijsdijk, Hultink & Diamantopoulos 2007). A good example of such Smart Product reactivity and adaptability could be a hair dryer that lowers the temperature of the hot air as the moisture of the hair falls, thereby preventing damage to the hairs (Rijsdijk, Hultink & Diamantopoulos 2007).

Proactivity. Apart from responsiveness, what makes a product smart is foremost the increasing ability to proactively partake in the user's plans and intentions (4) (Maass &

Varshney 2008; Mühlhäuser, Ferscha & Aitenbichler 2008). In this context, predictive analytics, as a technique that uses big data analytics to engage in proactive behavior, will significantly gain in importance when leveraging product smartness (Bolton 2018; Porter & Heppelmann 2014). The combined strength of analytics, statistics, and machine learning will allow creating increasingly accurate predictive models of the future which will drive the development of forthcoming Smart Products and, in Ultimo, help to strengthen customer-firm relationships (Bstieler et al. 2018; Gunasekaran et al. 2017; Porter & Heppelmann 2014).

Multifunctionality. Embedded in a larger internet of connected devices and equipped with AI and sensing capabilities, Smart Products become highly multifunctional (4). In earlier days, multifunctionality was explicitly excluded as a criterion for product intelligence by some authors (see Rijsdijk, Hultink & Diamantopoulos 2007), later, however, it found widespread inclusion in smartness conceptualizations (e.g., Novak & Hoffman 2018; Raff & Wentzel 2019; Rijsdijk & Hultink 2009). Multifunctionality allows intelligent products to assist its owners or users in a variety of different tasks (Rijsdijk & Hultink 2009). However, according to research, the aspect of multifunctionality is not entirely positive. In a series of studies, Rijsdijk and Hultink (2009) found that the degree of multifunctionality of a Smart Product significantly increases perceived complexity and risk, and only in some cases its perceived relative advantage. Hence, the authors suggest companies to only stepwise increase the functionality of products in order to allow the user to gently get used to them.

Customization. Smart Products can be characterized as highly customizable or personalized products (1). Maass & Varshney (2008) describe this as the “tailoring of products according to buyer’s and consumer’s needs and affects” (p. 2013). For example, smartphones or smart home assistants can actively be customized through a variety of available apps and skills. This enables a highly personalized consumer experience through the provision of tailored services (Allmendinger & Lombreglia 2005; Maass & Varshney 2008). Customization may also occur passively as a reaction to the user's preferences and habits, such as with the “Nest Sense” function of the Nest Learning Thermostat.

Fourth Level: Independent Action

The fourth level “Independent Action” captures the ability of products to actively engage in reasoning processes and act autonomously, sometimes even authoritatively, potentially driven by AI.

Autonomy and Self-Management. Smart Products are very frequently characterized by their ability to act autonomously and manage themselves (20) (e.g., Bstieler et al. 2018; Hoffman & Novak 2017; Novak & Hoffman 2018; Rijsdijk & Hultink 2009; Touzani et al. 2018). Rijsdijk & Hultink (2003) suggest an early definition for this aspect by characterizing it as the principle “that a product does not need human intervention but instead takes over on its own” (p. 206). In the dawn of the era of autonomous driving, product autonomy has received great attention – always moving between utopia and dystopia. Self-driving cars that respond automatically to high levels of traffic by alternative route guidance or impede accidents by activating the brakes and alerting the emergency services may soon be more than a futuristic vision (see also McGee 2019). To date, the literature distinguishes four levels of autonomy. Based on Baber's (1996) original work, Rijsdijk & Hultink (2003) apply the levels *manual level*, *bounded autonomy*, *supervised autonomy* and *symbiosis* to describe different degrees of product autonomy. Overall, however, product autonomy has received little attention in current research. An exception are Schweitzer and van den Hende (2016) who examine the relationship between the degree of perceived disempowerment and the adoption rate of autonomous products.

Reasoning and Decision-Making. According to several authors (11), the ability to make their own decisions and reasoning is at the core of product intelligence (Kortuem et al. 2010; Rijsdijk & Hultink 2009). Moreover, in order to empower the emergence of the IoT, it seems not only necessary to track the identity, location, movement, and condition of an intelligent product, but also to equip it with more complex capabilities, such as object-oriented complex decision-making, that enable it to (inter-) act independently (López et al. 2012). It is against this backdrop that, López et al. (2012) define: “Smart Objects are those objects that can make decisions about themselves and their interactions with external entities” (p. 295). In this context, it is crucial to note that the descriptive criterion “Reasoning and Decision-Making” is interrelated with facets of the aspect “Autonomy and Self-management”. A key prerequisite for independent decision-making are highest levels of autonomy (*supervised autonomy* or *symbiosis*) in conjunction with product intelligence (Valckenaers & van Brussel 2008), whereas at low levels of autonomy (*manual level* or *bounded autonomy*) no independent reasoning and decision making takes place (Meyer, Främling & Holmström 2009; Rijsdijk & Hultink 2009; Rijsdijk & Hultink 2003).

Actuation. Actuation (6) means to independently activate actions (e.g., Baird & Riggins 2016; Mani & Chouk 2017). Compared to reactivity, those do not represent reactions to the environment but deliberative and authoritative suggestions or actions based on AI and self-reinforcement machine learning (Silver et al. 2017; Novak & Hoffman 2018). An example is the AlphaGo Zero by Google's AI group DeepMind (Silver et al. 2017).

Fifth Level: Anthropomorphism

The fifth and highest level, “Anthropomorphism” refers to the ability of products to appear and interact in a human-like manner.

Anthropomorphism. Only three of the reviewed articles use a certain facet of anthropomorphism in their definition of a Smart Product (Raff & Wentzel 2019; Rijsdijk & Hultink 2009; Rijsdijk, Hultink & Diamantopoulos 2007). According to Rijsdijk, Hultink & Diamantopoulos (2007), a human-like-interaction means that Smart Products can communicate and interact “in a natural, human way” (p. 343) while a personality leads to Smart Products possessing the “ability to show the properties of a credible character” (p.343). Overall, this defining criterion stands for all the features that anthropomorphize technology products, thus, providing them with characteristics that are usually reserved for humans, such as sophisticated reasoning and intentions, autonomy, voice interaction, and a personality (Culley & Madhavan 2013). Remarkably, Novak & Hoffman (2018) whose idea of a Smart Product is largely based on the conceptualization by Rijsdijk, Hultink & Diamantopoulos (2007) explicitly delimit their conceptualization by this aspect. They state: “where our conceptualizations diverge is that Rijsdijk et al. (2007) assume human-centric anthropomorphism, while our framework does not require human-like interaction or personality to consider an object as smart” (p. 4). However, considering people’s increasing attempts to anthropomorphize technology (e.g., human-like service bots) we expect this to become a prevailing defining characteristic (Wirtz et al. 2018).

Bibliometric Analysis

The 19 basic defining criteria revealed from the literature review reflect the wide array of aspects that are applied by current research in the definition of Smart Products as an epistemic object. To further explore this topic and to identify specific points of divergence and blind spots in the literature, our SLR is supplemented by a bibliometric analysis (Palmatier, Houston & Hulland 2018). Importantly, the 19 defining criteria allow us to quantitatively compare extant conceptualizations of Smart Products on a standardized criterion level.

In order to perform a meaningful bibliometric analysis on the standardized criterion level, we calculated a conformity measure that indicates the similarity or consensus of the Smart Product conceptualizations used in the articles in our sample (Scheff 1967). A criterion matrix that relates each paper from our sample (rows) to the set of extracted criteria (columns) served as the starting point for the conformity measure (see Appendix C). An "x" in a cell $\mathrm{a}_{m,i}$ shows that the paper of row *m* lists the criterion of column *i* in its Smart Product definition. Our derived conformity score $CS(M,N)$ is based on the logic of the Jaccard similarity coefficient and relates the criteria-based intersection $(M \cap N)$ of two definitions of paper *M* and *N* to the union $(M \cup N)$ of both papers (Jaccard 1901; Leydesdorff 2008):

$$CS(M,N) = \frac{|M \cap N|}{|M \cup N|}$$

Thus $CS(M,N)$ represents the ratio between the number of commonalities and the sum of the overall considered properties of two papers that allows us to study the degree of consensus in our article sample. $CS(M,N)$ is calculated according to $\forall\, m = 1, \ldots, M$ and $\forall\, n = 1, \ldots, N$, with *M* = *N* = 37 representing each possible pairing of papers. $CS(M,N)$ may range from 0% (no conceptual unity at all) to 100% (complete conceptual unity).

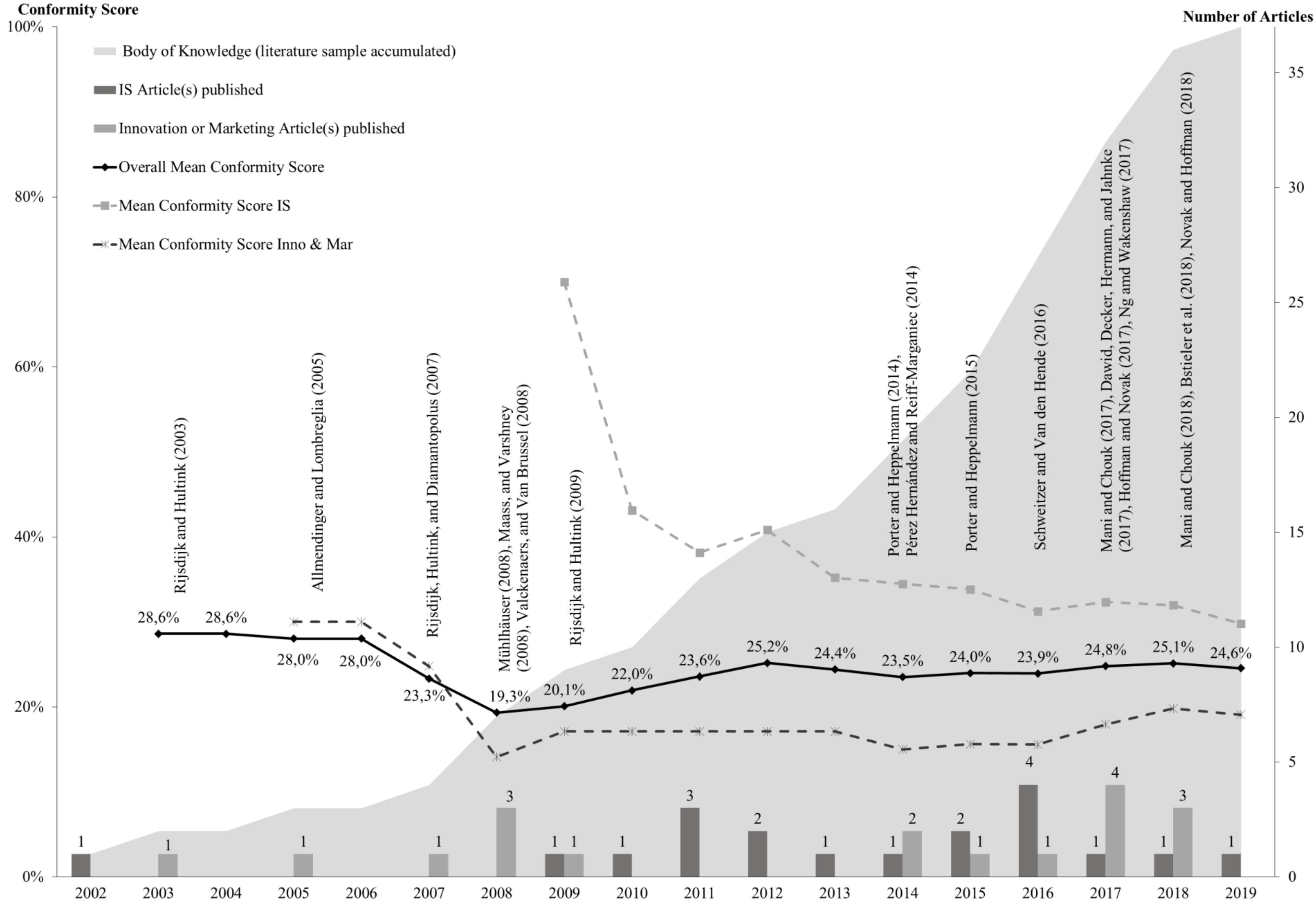

Figure 4. Bibliometric analysis

Figure 4 plots the evolvement of our computed conformity scores over time and maps the relevant publication points of the articles from the innovation and marketing field (Inno & Mar). Overall, the findings from our bibliometric analysis are in support of our initial observation of a scattered and patchy body of research suffering from a lack of consensus regarding what defines a Smart Product. As previously mentioned, from our content analysis, we revealed that 30 of the papers analyzed are based on either a combination of different previously established defining criteria or own ad-hoc conceptualizations. This initially revealed inconsistency is in line with the conformity score that we calculated for the 37 analyzed papers based on the standardized criteria. The overall mean score oscillates between rather low conformity levels of 19.3% and 28.6% over the considered time span, averaging on the level of 23.2% (sd = 6.4%). These numbers are a witness to the conceptual disagreement prevailing in the field. In addition, the analysis of the conformity score allowed us to pursue intra-disciplinary analyses, comparing our literature sample on the level of the research field. Figure 4 shows that the average conformity score of the IS field (m = 38.3%; sd = 11.3%) runs above that of the innovation and marketing field (m = 19.2%; sd = 4.9%), suggesting higher consensus regarding the respective conceptualizations of the Smart Product. However, these numbers have to be interpreted with caution as two articles from the beginning of the observation period (i.e., Wong et al. (2002); Meyer, Främling & Holmström (2009)) have relied on a very similar understanding of Smart Products, thus affecting the field's overall conformity score. In sum, the conformity scores for both research streams range at low levels and converge over time. In addition, Pearson correlation coefficients were computed to assess the relationship between the development of the total body of knowledge (cumulated number of articles in our sample) and the respective average conformity scores of the IS and innovation and marketing stream. Moderate to strong negative correlations were revealed ($r = -0.51$, $p < .05$ for innovation and marketing and $r = -0.85$, $p < .01$ for IS). This provides further evidence for the increasingly diverging conceptualizations in both fields, suggesting that with each article added to the field, the Smart Product as a concept gets fuzzier. In addition, we calculated the correlations between the appearance of the basic defining criteria and the age of the articles in order to identify criteria that have either arisen or disappeared over time (see detailed correlation matrix in Appendix D). We found significant positive correlations between the defining criteria of "Reasoning and Decision-Making" ($r = 0.46$, $p < .01$), "Proactivity" ($r = 0.34$, $p < .05$) and the age of the articles. This suggests that the more recent the studies in our sample was, the lesser these criteria tended to appear as defining features of Smart Products. Apart from this finding, the other basic defining aspects were applied fairly consistently over the period considered as they did not show significant correlations over time.

Discussion, Contributions and Implications [Directions]

As our analysis showed, the concept of a Smart Product means a lot of different things depending on who is asked – hardly surprising considering the multiple exciting viewpoints from which this phenomenon may be approached. In the service of integrating these perspectives and creating common ground for future research, we conducted an SLR. By this means, we achieved an overview of the commonly used characteristics of Smart Products as well as synthesized them into a hierarchical framework. Finally, a bibliometric analysis of the literature sample added robust support for our initial perception of an inconsistent body of knowledge and stressed the need for a shared conceptualization, within and across disciplines.

Overall, this study makes three important contributions to the literature. First, by looking across the borders of different disciplines, this SLR contributes to a broader understanding and synthesis of existing conceptualizations of Smart Products (MacInnis 2011). More specifically, the currently scattered and patchy body of knowledge is systematically condensed from 60 defining criteria into 5 Smart Product levels containing a standardized set of 19 basic defining criteria for Smart Products. Second, this set of basic defining criteria contributes through a standardized terminology for Smart Products which supports a more structured dialogue about the concept. In other words, it brings about the required structure and comparability to a field that is yet standing on feet of clay and provides a standardized springboard for further cumulative research endeavours (Hirsch & Levin 1999).

Second, the hierarchical levels in our framework provide a Smart Product logic from which, for example, it can be deduced that products that possess IoT capabilities are not necessarily intelligent at the same time which is often misrepresented or viewed as being the same by current research. Thus, in future research, our framework may serve to improve the incorporation of the concept of Smart Products into other conceptualizations, such as the IoT or smart services (Ng & Wakenshaw 2017; Oberländer et al. 2017).

Third, the present review provides a representative state-of-the-art snapshot containing – to the best of our knowledge – all relevant, peer-reviewed articles on Smart Products. In addition, from a method perspective, we contribute through the introduction of a criterion-based approach that enables comparisons of an interdisciplinary set of articles based on their underlying conceptualizations of Smart Products. The conformity score measure applied in this study helps to trace the emergent meanings of a term within and across disciplines in a way that was heretofore not possible. This feeds the repeated calls for research beyond disciplinary boundaries as well as the application of new methods in smart technology and IoT research (Bstieler et al. 2018; Mani & Chouk 2018; Noble & Spanjol 2019). Moreover, it allows us to reveal discrepancies and blind spots which in turn may guide future research endeavours (Barczak 2017; Bstieler et al. 2018; Palmatier, Houston & Hulland 2018).

In the next sections, additional implications for research and practice are provided based on our observation of the body of research. Thereby, we carve out relevant facets that may guide further research in order to advance theoretical understanding and practical use.

Implications for Research

Moving from dustbowl empiricism to theoretical rigor and depth. Our work reveals that current research on Smart Products lacks a consensual theoretical framing and is suffering from dustbowl empiricism[2]. As in many emerging fields, empirical research endeavors such as by Raff & Wentzel (2019) or Touzani et al. (2018) are important in the exploration phase of novel technologies and concepts. Yet, we encourage future research to now take a step back, take stock of existing work, and contribute to the provision of a common rigorous theoretical foundation that is necessary for the creation of a cumulative body of knowledge (Astley 1985; Noble & Spanjol 2019; Webster & Watson 2002). Our bibliometric analysis shows that the current body of knowledge across the research streams largely suffers from a lack of consensus regarding their underlying understanding of Smart Products (see Figure 4). Thus, although the sheer amount of 29 theoretical contributions in our sample indicates that some good effort has been made to revise and recast the research field, these efforts have apparently

[2] An approach to science and the social sciences consisting primarily of making empirical observations and collecting data rather than establishing a theoretical framework (Vandenbos, 2015).

not led to the creation of consensual frameworks and concepts. In addition, as can be seen from Table 1, although the field is very interdisciplinary in nature, the different research streams from innovation, marketing and IS rarely draw on concepts beyond their disciplinary boundaries. Whilst Ng & Wakenshaw (2017) hoped to "persuade researchers to actively engage in interdisciplinary IoT research" (p. 4), only a few attempts to consolidate different interdisciplinary perspectives have been made. Examples of such attempts are Herterich & Mikusz (2016) who conceptualized "digital artifacts" by integrating different research streams across IS and innovation research as well as Marikyan, Papagiannidis & Alamanos (2019) who conduct an interdisciplinary literature review in the domain of the smart home. We urge researchers to follow these lines with full vigor and to develop frameworks and conceptualizations of the Smart Product that integrate adjacent research streams. Only what is conceptually clear may represent a solid epistemic object of investigation for future research and thus can add to the research field's vitality (MacInnis 2011). Thus, taking that step back may result in construct clarity and thus, in the long run, can pave the way for the advancement of a solid cumulative research tradition.

New perspectives through methodological pluralism and method diversity. The empirical works in our sample mostly take a consumer/user-perspective and try to explain the (nomological) paths shaping behavioral responses and usage intentions with respect to Smart Products (See Table 1 and Appendix A). Thereby, these articles usually do not look at Smart Products holistically, but pursue an isolated consideration of one of the characteristics of Smart Products such as "autonomy" (Rijsdijk & Hultink 2003; Schweitzer & van den Hende 2016), "connectedness" (Touzani et al. 2018) or "intelligence" (Rijsdijk, Hultink & Diamantopoulos 2007) and are driven by practical relevance and trending topics such as the smart home (Mani & Chouk 2018; Mani & Chouk 2017; Mayer et al. 2011; Raff & Wentzel 2019). There is no doubt that these are relevant articles for the field. However, our observation is that research on Smart Products fails to break new grounds in terms of (i) conceptual perspectives such as technologized innovation processes, service innovations through Smart Products, broader service-ecosystems, and relationships (for an exception see Hoffman & Novak (2017)); and (ii) methodologies and research approaches such as mixed-method research (Johnson & Onwuegbuzie 2004). Current empirical research tends to mostly reiterate existing patterns from their respective fields and thus fails to contribute with new and surprising insights.

However, in order to push the boundaries, to reveal surprising insights as well as to fathom the full picture of the behavioral reactions with regard to multifaceted Smart Products, we urgently call for novel perspectives. These may be induced through the expansion of the methodological repertoire, mixed-method research approaches, or by establishing new links with other fields of research (Bstieler et al. 2018; Venkatesh, Brown & Bala 2013). In this respect, mixed-method research may prove particularly useful due to the combination of inductive-exploratory and deductive-explanatory studies (Creswell & Plano Clark 2018). Due to the fact that these approaches allow to grasp the focal concept more holistically – similar to recent developments in the IS field (see Valacich & Brown 2018; Venkatesh, Brown & Bala 2013; Venkatesh, Brown & Sullivan 2016) – we believe that research on the complex concept of Smart Products would greatly benefit from methodological pluralism and method diversity.

Surprising blind spots. Surprisingly, in our bibliometric analysis, we found that the aspects of “Reasoning and Decision-Making” and “Proactivity” faded out over time and found lesser and lesser application in current Smart Product characterizations (see also Appendix D). This seems counter-intuitive in light of the increasing trend of autonomously acting products and predictive analytics in Smart Products (Bstieler et al. 2018). Whereas practice increasingly moves towards integrated decision-making capabilities and predictive analytics in their service and product offerings (e.g., predictive maintenance and schedule planning at the German Deutsche Bahn AG (Cintona 2016)), research contributions beyond mere research calls such as by Bstieler et al. (2018) remain limited (for recent exceptions see: Bradlow et al. (2017) or Kakatkar & Spann (2018)). Thus, we find that these currently under-investigated aspects represent promising starting points for future research. Moreover, the aspect “Anthropomorphism” found very little attention in our literature sample (3 total mentions). However, as technology such as Apple’s Siri or Amazon’s Alexa gets more and more anthropomorphic, this aspect has to become inseparably linked to the notion of Smart Products (Wirtz et al. 2018). Thus, we call research to focus on these aspects, include them into Smart Product conceptualizations as well as to study their diverse effects and behavioral reactions.

Establish two-step conceptualization funnels. Bringing forth a standardized framework might have been the easier part of the journey, but to establish it in the long run will be more challenging. Especially in marketing and innovation research as our analysis shows, researchers rely on a wide array of diverging conceptualizations for Smart Products (see Table 1). To overcome this hindrance, we suggest the use of a two-step funnel approach in future characterizations of Smart Products. This means, in a first step, that future research should draw from our suggested framework and terminology, in order to define the general understanding of the Smart Product as well as to connect it with its overall intellectual core. In a second step, adaptions to this terminology can be made to meet the researchers' needs. This approach may enable a more systematic way for future research endeavors and may help scholars to deal with the steadily increasing complexity of Smart Product assemblages (Novak & Hoffman 2018).

What makes a product smart? This work contributes by standardizing current perspectives on the defining criteria of Smart Products, providing a normalized perspective on the state of the art of the extant research (see Table 2 and Figure 4). An interesting question related to the breadth of the Smart Product concept, as we observed in our research sample, is "When is a product smart and when is it not smart?" This question may include – but not be limited to – to finer grained considerations such as "Is product smartness a continuum or binary (smart/non-smart)?" In this context, our Smart Product hierarchy could also be used by future research to address sometimes mistakenly held shared mental models such as equating the IoT Product and the Smart Product or naming them in the same breath (e.g., Kuijken, Gemser & Wijnberg 2017). IoT capabilities such as being able to communicate and exchange information are a prerequisite to making a product smart in the sense of independent reasoning or decision-making. However, a product does by no means have to be smart in order to be IoT-capable. Although some researchers have already started to tackle them (e.g., Alter 2018; Herterich & Mikusz 2016), from our perspective, there is enough room for future research to further sharpen the Smart Product conceptualization and elaborate more on these issues. In this regard, our framework may represent a point of departure for such endeavors.

Managerial Implications

Filling a buzzword with life. Our hierarchical framework may help practitioners to fill the term "Smart Product" with life. Thus, especially Smart Product newbies, i.e. firms that have not yet but are planning to digitize their business models, may find a good baseline in our framework helping them to navigate in the complex Smart Product world. This may be for two reasons. First, it can be used to leverage the firm-internal understanding and dissemination on what a Smart Product is by using a common framework of reference. As hype topics often create a veritable flood of terminologies this can help to make the current buzzword more tangible. The current situation is reminiscent of the time when Customer Relationship Management (CRM) became a rising phenomenon (Zablah, Bellenger & Johnston 2004). At the time, practice greatly benefitted from the interdisciplinary synthesis of differing understandings towards an integrated conceptualization of CRM (Zablah, Bellenger & Johnston 2004). Second, along with the derived set of defining criteria, each in itself may represent a good starting point and food for ideas from which use-cases can be structured to showcase the far-reaching potential benefits and opportunities of Smart Products (e.g., data-driven new product development (NPD) (Jernigan & Ransbotham 2016; Porter & Heppelmann 2014).

Support for privacy or security risk assessments. It can be expected that third-party institutions will soon guarantee and certify if Smart Products fulfil certain mandatory requirements and provide adequate protection of the consumer or user (Ala-Honkola 2018). As our framework provides a comprehensive, but yet concise overview of the complete Smart Product functioning stack, illustrating what a Smart Product is potentially capable of doing, it may support organizations to improve the completeness and consistency of their internal privacy or security risk assessments as well as to detect potential misalignments.

Conclusion

The overall objective of this work was to shed light on the current body of knowledge and the existing conceptualizations of Smart Products as well as to reveal the basic defining criteria currently applied. Taking stock of our work, we acknowledge the fact that Smart Products currently are (and presumably will be) studied by different scholars from different fields using diverging perspectives that suit their research questions.

Thus, to date, these diverging demarcations have led to a highly scattered and patchy body of knowledge. After reviewing the major perspectives on Smart Products, this paper puts forth as a take-home a hierarchical framework for Smart Products. This framework attempts not only to standardize the hazy concept of the Smart Product as an epistemic thing but also to merge the diverging terms applied by scholars into a hierarchical logic and a precise common language (Klein & Hirschheim 2003).

Taken together, the Smart Product in its current form represents a rather elusive concept that may be endangered by construct collapse (Hirsch & Levin 1999). Besides, due to the dynamic nature of the concept it seems likely that it will continue to be a moving target (Rheinberger 1997). However, we would argue that it is possible and fruitful alike to generalize about Smart Products, if these conceptualizations are understood as generative and fluid epistemic objects that make reference to a common terminology that – at the same time – leaves enough room for research- or time-specific refinements (Yoo, Henfridsson & Lyytinen 2010; Yoo 2013). This will allow the epistemic object to emancipate itself without losing its roots in oblivion – and thus to be faithful to its intellectual core as well as the idea of cumulative research.

Lastly, our work should be interpreted in light of its limitations. Both the search process with regard to the formulation of the search string as well as the compilation of the paper sample and the extraction of the relevant description criteria are based on subjective assessments. We are aware that personal interpretations and assessments of relevance could have affected the aggregation and coding of the criteria in this work. In addition, while we conducted a systematic literature search based on keywords, there is still the possibility that we missed out a portion of the relevant literature in particular in terms of publications not listed in the WoS database. Lastly, a further limitation might stem from the sampling procedure in the form of a broad funnel instead of taking a narrow focus on a specific product category or market. These issues are, however, common to SLRs (Córdoba, Pilkington & Bernroider 2012; Webster & Watson 2002).

As has become apparent, the Smart Product is a rapidly evolving and multifaceted concept, developing at the same speed as IT and NPD move forward. In the mess of concepts and fast-evolving phenomena that underlie the fields of innovation, marketing, and IS lies the potential. It is what allows the fast-paced research that guarantees their vitality. However, at some point scholars have to integrate and take stock of entire swathes of prior knowledge in order to keep the orientation in the midst of related concepts as well as to provide the field with a state of the art snapshot it can build upon (Palmatier, Houston & Hulland 2018). This work should provide a solid platform for the advancement of a more cumulative research tradition which is surely indispensable for the further development of the body of knowledge on Smart Products.

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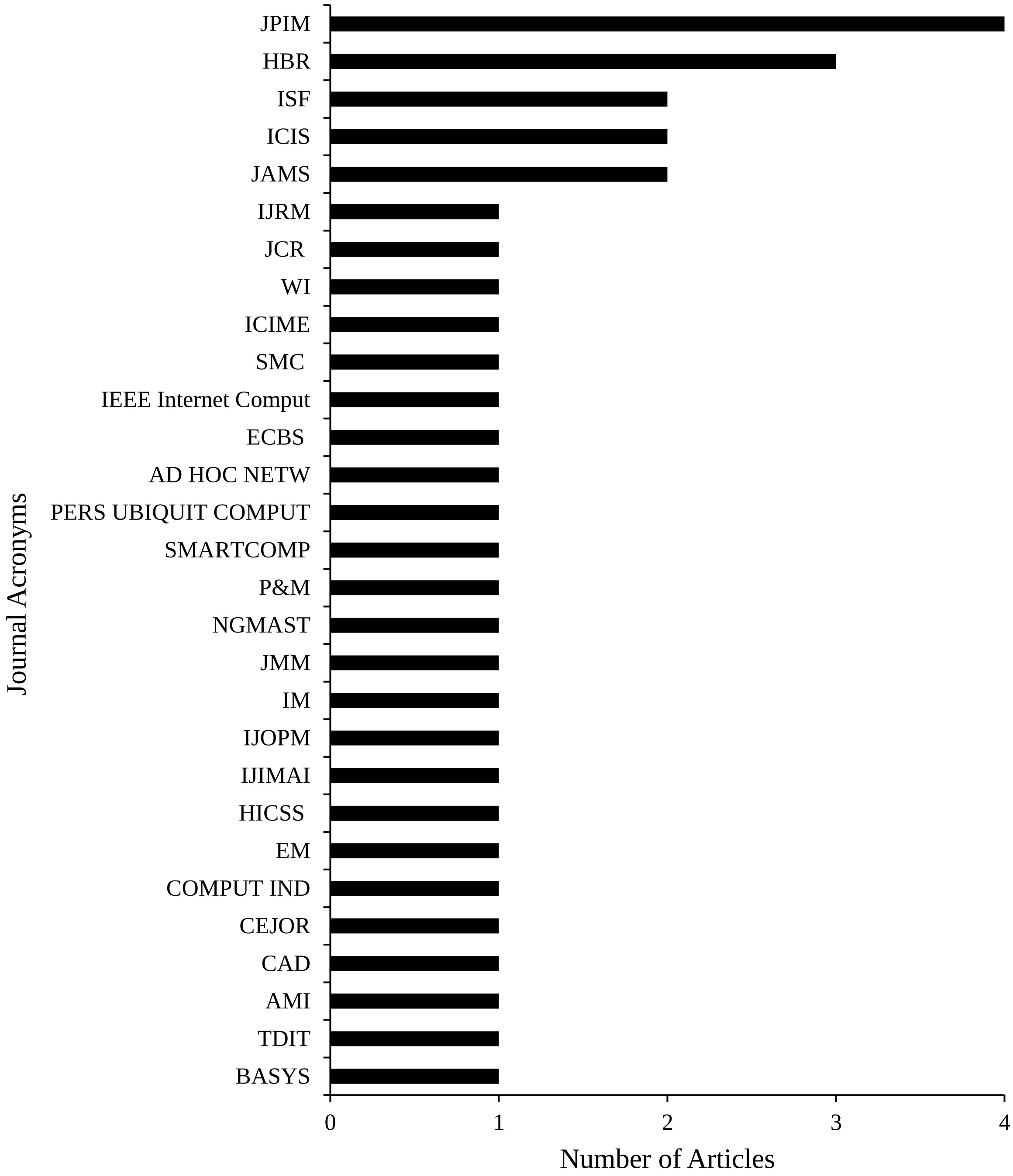
Appendix Essay I

Appendix A. Final Literature Sample

Authors	Year	Title	Type of Paper	Journal
Wong, McFarlane, Zaharudin and Agarwal	2002	The Intelligent Product driven supply chain	Theoretical	IEEE SMC
Rijsdijk and Hultink	2003	Honey, Have You Seen Our Hamster? Consumer Evaluations of Autonomous Domestic Products	Empirical	JPIM
Allmendinger and Lombreglia	2005	Four strategies for the age of Smart Services	Theoretical	HBR
Rijsdijk, Hultink, and Diamantopolus	2007	Product intelligence: its conceptualization, measurement and impact on consumer satisfaction	Theoretical	JAMS
Mühlhäuser	2008	Smart Products: An Introduction	Theoretical	AmI 2008
Maass and Varshney	2008	Preface to the Focus Theme Section Smart Products	Theoretical	Electron. Mark.
Valckenaers and Van Brussel	2008	Intelligent Products: Intelligent beings or agents?	Theoretical	BASYS
Rijsdijk and Hultink	2009	How Today's Consumers Perceive Tomorrow's Smart Products	Empirical	JPIM
Meyer, Främling, and Holmström	2009	Intelligent Products: A survey	Theoretical	COMPUT IND
Kortuem, Kawsar, Fitton and Sundramoorthy	2010	Smart Objects as Building Blocks for the Internet of Things	Theoretical	IEEE Internet Comput
Kiritsis	2011	Closed-loop PLM for Intelligent Products in the era of the Internet of things	Theoretical	CAD
López, Ranasinghe, Patkai, and McFarlane	2011	Taxonomy, technology, and applications of Smart Objects	Theoretical	ISF
Mayer, Volland, Thiesse, and Fleisch	2011	User acceptance of Smart Products: an empirical investigation	Empirical	WI 2011
López, Ranasinghe, Harrison, and McFarlane	2012	Adding sense to the Internet of Things An architecture framework for Smart Objective systems	Theoretical	PERS UBIQUIT COMPUT
Miorandi, Sicari, De Pellegrini and Chlamtac	2012	Internet of things: Vision, applications, and research challenges	Theoretical	AD HOC NETW
Gutierrez, Garbajosa, Diaz, and Yague	2013	Providing a Consensus Definition for the Term “Smart Product"	Theoretical	ECBS
Porter and Heppelmann	2014	How smart, Connected Products Are Transforming Competition	Theoretical	HBR
Meyer, Buijs, Szirbik, and Wortmann	2014	Intelligent Products for enhancing the utilization of tracking technology in transportation	Theoretical	IJOPM
Pérez Hernández and Reiff-Marganiec	2014	Classifying Smart Objects using Capabilities	Theoretical	SMARTCOMP 2014
Porter and Heppelmann	2015	How Smart, Connected Products Are Transforming Companies	Theoretical	HBR
Whitmore, Agarwal, and Xu	2015	The Internet of Things—A survey of topics and trends	Theoretical	ISF
Dorsemaine, Gaulier, Wary, Kheir, and Urien	2015	Internet of Things: a definition and taxonomy	Theoretical	NGMAST 2015
Schweitzer and Van den Hende	2016	To Be or Not to Be in Thrall to the March of Smart Products	Empirical	PandM
Baird and Riggins	2016	A Resource Complementarity View (RCV) of Value Creation in the Context of Connected Smart Devices	Theoretical	HICSS 2016
Püschel, Schlott, and Röglinger	2016	What’s in a Smart Thing development of a multilayer taxonomy	Theoretical	ICIS 2016
Herterich and Mikusz	2016	Looking for a Few Good Concepts and Theories for Digitized Artifacts and Digital Innovation in a Material World	Theoretical	ICIS 2016
Holler, Uebernickel, and Brenner	2016	Understanding the Business Value of Intelligent Products for Product Development in Manufacturing Industries	Empirical	ICIME 2016
Mani and Chouk	2017	Drivers of consumers' resistance to Smart Products	Empirical	JMM
González García, Meana-Llorián, Pelayo G-Bustelo, and Cueva Lovelle	2017	A review about Smart Objects, Sensors, and Actuators	Theoretical	IJIMAI
Dawid, Decker, Hermann, Jahnke, Klat, König, and Stummer	2017	Management science in the era of smart consumer products: challenges and research perspectives	Theoretical	CEJOR
Hoffman and Novak	2017	Consumer and Object Experience in the Internet of Things: An Assemblage Theory Approach	Theoretical	JCR
Ng and Wakenshaw	2017	The Internet-of-Things: Review and research directions	Theoretical	IJRM
Mani and Chouk	2018	Consumer Resistance to Innovation in Services: Challenges and Barriers in the Internet of Things Era	Empirical	JPIM
Touzani, Charfib, Boistel, and Niort	2018	Connecto ergo sum! an exploratory study of the motivations behind the usage of connected objects	Empirical	IM
Bstieler, Gruen, Akdeniz, Brick, Du, Guo, Khanlari, McIllroy, O’Hern, and Yalcinkaya	2018	Guest Editorial: Emerging Research Themes in Innovation and New Product Development: Insights from the 2017 PDMA-UNH Doctoral Consortium	Theoretical	JPIM
Novak and Hoffman	2018	Relationship journeys in the internet of things: a new framework	Theoretical	JAMS
Raff and Wentzel	2019	A Cognitive Perspective on Consumers’ Resistances to Smart Products	Empirical	TDIT 2018

Appendix B. Academic Literature Outlets in the Final Literature Sample



Appendix C. Overarching Levels and Basic Definition Criteria of the Analyzed Papers

	Overarching Levels and Principal Defining Criteria																		
	(1) Hardware and Data Management				(2) IoT Capabilities					(3) Sensing, Reacting, and Anticipating						(4) Independent Action			(5) Anthropomorphism
Article	IT Equipped Physical Object	Data Capturing and Tracking	Data Processing and Analysis	Data Storage (Hardware or Cloud)	Data Provision and Transmission	Unique Identification	Networking and Connectivity	Communication and Information Exchange	Interaction and Cooperation	Sensing	Real-Time Context-Awareness	Reactivity and Adaptability	Proactivity	Multi-functionality	Customization	Autonomy and Self-Management	Decision-Making and Reasoning	Actuation	Anthropomorphsim
Wong, McFarlane, Zaharudin, and Agarwal (2002)		x		x	x	x		x								x	x		
Allmendinger and Lombreglia (2005)		x	x		x					x						x			
Rijsdijk, Hultink, and Diamantopolus (2007)									x			x				x			x
Mühlhäuser (2008)					x		x	x	x		x		x				x		
Maass and Varshney (2008)							x	x			x	x	x		x				
Valckenaers and Van Brussel (2008)	x										x						x		
Rijsdijk and Hultink (2009)									x			x		x		x			x
Meyer, Framling, and Holmström (2009)		x		x	x	x		x	x			x	x			x	x		
Kortuem, Kawsar, Fitton, and Sundramoorthy (2010)	x	x	x		x		x	x	x	x						x	x		
Kiritsis (2011)			x	x				x		x							x		
López, Ranasinghe, Patkai, and McFarlane (2011)				x	x	x	x	x	x	x							x		
Mayer, Volland, Thiesse, and Fleisch (2011)	x	x			x		x		x	x	x	x	x			x			
López, Ranasinghe, Harrison, and McFarlane (2012)				x	x	x		x	x	x							x		
Miorandi, Sicari, De Pellegrini, and Chlamtac (2012)	x		x			x	x	x		x						x	x	x	
Rijsdijk and Hultink (2003)			x					x				x				x			
Gutierrez, Garbajosa, Diaz, and Yagüe (2013)			x				x				x					x			
Porter and Heppelmann (2014)	x		x	x			x			x									
Meyer, Buijs, Szirbik, and Wortmann (2014)	x	x		x					x							x	x		
Pérez Hernández and Reiff-Marganiec (2014)	x			x		x	x	x											
Whitmore, Agarwal, and Xu (2015)	x		x			x	x	x		x									
Dorsemaine, Gaulier, Wary, and Kheir (2015)			x	x	x		x	x		x								x	
Schweitzer and Van den Hende (2016)	x								x							x			
Porter and Heppelmann (2016)	x		x	x			x			x									
Baird and Riggins (2016)	x	x	x		x		x	x		x		x						x	
Püschel, Schlott, and Röglinger (2016)	x						x	x	x	x									
Herterich and Mikusz (2016)	x																		
Holler, Uebernickel, and Brenner (2016)	x		x	x			x	x		x							x		
Ng and Wakenshaw (2017)						x	x												
Mani and Chouk (2017)		x					x			x						x		x	
Gonzalez Garcia, Meana-Llorian, Pelayo G-Bustelo, and Cueva Lovelle (2017)	x		x			x	x	x	x	x						x		x	
Dawid, Decker, Hermann, and Jahnke (2017)	x	x	x		x			x		x								x	
Hoffman and Novak (2017)	x	x	x				x	x	x	x						x			
Mani and Chouk (2018)	x		x	x				x	x							x			
Bstieler, Gruen, Akdeniz, Brick, Du, Guo, Khanlari, McIllroy, O'Hern, and Yalcinkaya (2018)		x	x		x				x			x				x			
Novak and Hoffman (2018)									x			x		x		x			
Touzani, Charfi, Boistel, and Niort (2018)		x	x		x		x		x							x			
Raff and Wentzel (2019)									x			x		x		x			x
SUM	18	12	17	12	13	9	20	21	18	18	5	10	4	3	1	20	11	6	3

Appendix D. Coefficients of Correlations

Variable	**Coefficients of Correlations**																			
	Age	Communication and Information Exchange	Autonomy and Self-Management	Networking and Connectivity	Sensing	IT Equipped Physical Object	Data Processing and Analysis	Interaction and Cooperation	Data Provision and Transmission	Data Storage (Hardware or Cloud)	Data Capturing and Tracking	Reasoning and Decision-Making	Reactivity and Adaptability	Unique Identification	Actuation	Real-Time Context-Awareness	Proactivity	Anthro-pomorphism	Multi-functionality	Customization
Age	**—**	**0.10**	**0.07**	**-0.23**	**-0.10**	**-0.32**	**-0.26**	**-0.08**	**0.29**	**0.08**	**0.07**	**,458****	**0.09**	**0.13**	**-0.26**	**0.32**	**,336***	**0.16**	**-0.13**	**0.19**
Communication and Information Exchange		—	-0.31	0.24	,355*	0.14	0.25	-0.08	0.22	0.29	-0.06	,362*	0.32	,396*	0.26	-0.11	0.15	-0.32	-0.32	0.15
Autonomy and Self-Management			—	-0.31	-0.30	-0.19	0.03	,463**	0.00	-0.29	,407*	-0.11	0.32	-0.11	-0.04	-0.11	-0.03	0.27	0.27	-0.18
Networking and Connectivity				—	,463**	0.25	0.25	-0.19	0.00	-0.06	-0.06	-0.11	-0.29	0.14	0.26	0.21	0.15	-0.32	-0.32	0.15
Sensing					—	,351*	,459**	-0.19	0.19	0.13	0.13	0.08	-,349*	0.08	,452**	-0.23	-0.16	-0.29	-0.29	-0.16
IT Equipped Physical Object						—	0.24	-0.08	-0.26	0.02	0.02	-0.04	-,349*	-0.05	0.16	-0.07	-0.16	-0.29	-0.29	-0.16
Data Processing and Analysis							—	-0.30	0.08	0.02	0.13	-0.16	-0.23	-0.17	0.31	-0.23	-,339*	-0.29	-0.29	-0.16
Interaction and Cooperation								—	0.19	-0.10	0.13	0.08	0.26	-0.05	-0.28	-0.07	0.18	0.31	0.31	-0.16
Data Provision and Transmission									—	0.09	,579**	0.26	0.06	0.11	0.14	0.04	0.29	-0.22	-0.22	-0.12
Data Storage (Hardware or Cloud)										—	-0.11	,434**	-0.29	0.28	-0.15	-0.27	-0.06	-0.21	-0.21	-0.12
Data Capturing and Tracking											—	0.05	0.10	-0.12	0.17	-0.10	0.13	-0.21	-0.21	-0.12
Reasoning and Decision-Making												—	-0.26	0.32	-0.13	0.09	0.15	-0.19	-0.19	-0.11
Reactivity and Adaptability													—	-0.20	-0.10	0.12	,376*	,488**	,488**	0.27
Unique Identification														—	0.09	-0.22	0.01	-0.17	-0.17	-0.09
Actuation															—	-0.17	-0.15	-0.13	-0.13	-0.07
Realtime Context-Awareness																—	,626**	-0.12	-0.12	,422**
Proactivity																	—	-0.10	-0.10	,479**
Anthropomorphism																		—	,637**	-0.05
Multifunctionality																			—	-0.05
Customization																				—

$*p \leq .05$ $**p \leq .01$

ESSAYII

"Wait, That's Creepy!"– A Mixed-Methods Study on Resistance to Intelligent Assistants*

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"WAIT, THAT'S CREEPY!"

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A MIXED-METHODS STUDY ON RESISTANCE TO INTELLIGENT ASSISTANTS

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Abstract

Empowered by artificial intelligence, intelligent assistants (IA) are rapidly finding their way into people's homes. While existing studies have typically focused on the benefits of IA, there is little research on why consumers may decide to actively resist these technologies. Against this background, the purpose of this mixed-methods study is twofold: The first study seeks to open the black box of people's minds using mental models to comprehensively identify belief structures and mechanisms that may promote resistance. The second study aims to quantitatively test the findings from Study 1 in a contextualised research model. The main findings of this research consist of a mental model that includes a comprehensive set of inhibitors and a quantitative validation of the nomological paths that shape the resistance to IA. This study contributes through the integration of different strands within resistance theory. Moreover, it comprehensively identifies a range of inhibitors to IA, including original, technology-specific inhibitors such as "feeling creeped out". Amongst others, our findings suggest that consumers have a built-in creepiness detector that warns them to stay away from intelligent technologies. For practice, our results provide valuable starting points to tackle potential resistance to IA and AI-empowered household technology at large.

Keywords: *Technology resistance, mental model, active resistance, artificial intelligence, internet of things*

Introduction

> "Increasingly, technologies spurred by the "Internet of things" are being specifically designed and developed for household customers. However, few studies have examined the adoption or diffusion of household technologies, resulting in gaps in our understanding of why and how consumers adopt (or do not adopt) such novel (and often complex) technologies" (Wunderlich, Veit & Sarker 2019 p. 673)
>
> "While IoT offers many bright benefits, it also has a dark side." (Shim et al. 2019 p. 5)

Driven by advancements in technology, smart artefacts are becoming paramount in the era of the Internet-of-Things (IoT) (Oberländer et al. 2017; Wunderlich, Veit & Sarker 2019; Yoo 2010). Especially intelligent assistants such as the Amazon Echo or Alphabet Inc.'s Google Home speaker are at the forefront of the recent flood of AI-empowered household technologies (Dawar & Bendle 2018).

Intelligent assistants (hereinafter referred to as IA) can be defined as voice-controlled devices that react and respond to user queries, engage in human-like behaviour, connect with other IoT devices as well as learn and evolve via machine learning capabilities (Mallat, Tuunainen & Wittkowski 2017). Empowered by AI, these assistants have a unique and distinct position compared to other technologies previously studied in the IS field, both from a user's as well as from a practitioner's perspective. For users, IA increase everyday convenience by providing a multitude of fine-tuned personalised services (Dawar & Bendle 2018; Mallat, Tuunainen & Wittkowski 2017). For practitioners, IA represent an interface technology that bears the potential to fundamentally foster datafication, the provision of personalised services as well as the advent of the smart home as a whole (Dawar & Bendle 2018; Grace et al. 2019; Lycett 2013). The successful adoption of IA may thus represent a tipping-point with the adoption of IA resulting in up- and cross-selling of other connected devices.

Despite the promising potential of IA, consumers' responses to this technology may not necessarily be positive. Recent reports of negative incidents with IA, such as the unannounced sending of call records to private contacts or eerie laughter sounds in the middle of the night (e.g., Shaban 2018), may trigger negative feelings and lead to resistance to adopting IA (Cremer, Nguyen & Simkin 2017; Shim et al. 2019). Hence, IA may also have a "dark side" that may undermine their successful diffusion. However, despite the great scholarly interest in IoT in general and IA in particular, there is – to the best of our knowledge – little research that has examined these technologies from the perspective of technology resistance (see also Wunderlich, Veit & Sarker 2019). This is in line with the general trend in IS research to approach new digital technologies from the perspective of *technology as a solution* but not from the perspective of *technology as a cause of problems* (Rowe 2018).

To gain an accurate understanding of the adoption process of IA, research thus needs to move beyond the theories that are typically used in the IS field to examine technology adoption. As such, models like the TAM (Davis 1989) exclusively consider those factors that promote technology adoption but neglect those that may inhibit adoption (Bhattacherjee & Hikmet, 2007). However, as adoption and usage typically depend on the interplay of enabling and inhibiting factors, these models may not provide a sufficiently holistic picture (Cenfetelli 2004).

Moreover, most technology acceptance studies are targeted at people who have actually experienced the technology in question (e.g., Moriuchi 2019; Strader, Ramaswami & Houle 2007). In many cases, however, the decision to adopt a technology is not based on people's actual experiences with that technology. Instead, their decisions may be strongly shaped by their *mental models*. These mental models represent the naïve conceptions and beliefs regarding a technology based on what people hear, infer and construe without necessarily correctly and appropriately representing real causalities and conditions (Bagozzi & Lee 1999; Vandenbosch & Higgins 1996). Hence, to achieve a deeper understanding of the nature of people's resistance to IA, it is also essential to first explore the complex and sometimes decontextualised inhibiting conceptions that people hold in their mental models (Złotowski, Yogeeswaran & Bartneck 2017).

In this research, we address this gap in the literature. Drawing on research on mental models and the dual-factor model of resistance, we examine the adoption decision process for IA with a specific focus on those factors that inhibit adoption. In particular, we focus on the functional and psychological barriers that arise when potential customers *actively* reflect about IA and then *deliberately* opt against adoption. Unlike more passive forms of innovation resistance (e.g., status-quo satisfaction), these inhibitors arise from the innovation itself and take effect when the consumer actively reflects on them (Heidenreich & Kraemer 2016). Examining the nature and the effects of these inhibitors is not only of theoretical interest but may also be important for practice. As such, failure rates for high-tech innovations typically range between 40–50% (Castellion & Markham 2013). Against this background, identifying the inhibitors to adoption may help companies in effectively stimulating the diffusion of IA.

Given the exploratory nature of our research endeavour, we pursue a developmental mixed-methods approach with two sequential studies, both qualitative and quantitative in nature, that build on each other (Creswell & Plano Clark 2018; Walsh 2015). In doing so, we follow the calls for the application of new research methods and mixed-method approaches in the IS domain (Ågerfalk 2013; Te'eni et al. 2015; Venkatesh, Brown & Bala 2013).

Study 1 seeks to inductively explore the mechanisms underlying the resistance to IA. It applies mental models to comprehensively elicit the cognitive structures and conceptions from people who have actively decided not to adopt IA. Study 1 is guided by the following research question:

(1) What are the constructed ideas and beliefs that drive the resistance to IA?

Our quantitative Study 2 aims to deductively confirm the accuracy and generalisability of our qualitative findings (Creswell & Plano Clark 2018; Venkatesh, Brown & Bala 2013; Walsh 2015). To achieve this, Study 1 and 2 are combined in an exploratory-sequential design where the qualitative insights from our first study inform the emergence of the research model for Study 2 (Creswell & Plano Clark 2018). Study 2 is guided by the following research question:

(2) What are the nomological paths that shape resistance to IA?

The remainder of the paper is organised as follows: First, the underlying conceptual background of the paper is outlined. The subsequent section presents the two studies and their results. In the concluding section, we derive implications for research and practice.

Theoretical Background: Dual-factor Model as a Lens

Most of the studies on technology acceptance and adoption assume that consumers are generally receptive to new technologies and have first-hand experience with a new technology such as IA (e.g., Koufaris 2002; Moriuchi 2019; Strader, Ramaswami & Houle 2007). This pro-innovation bias, however, tends to overshadow the reality of substantial (high-tech) innovation failure rates (Castellion & Markham 2013; Heidenreich & Kraemer 2016). In view of this, it is crucial to overcome such pro-innovation bias and to obtain a deeper understanding of resistance with respect to IA and its underlying drivers.

In contrast to *acceptance*, which represents factual behaviour, *resistance* can be conceived as a cognitive force that precludes such behaviour (Bhattacherjee & Hikmet 2007; Lewin 1947). In this respect, *resistance* has to be conceptually distinguished from *non-usage*. Non-usage means that individuals are simply unaware of a new technology, are still evaluating it or have already chosen to use it, but have postponed the purchase to some point in the future (Bhattacherjee & Hikmet 2007). Moreover, we focus on the concept of *active resistance* which can be conceptually distinguished from *passive resistance* (i.e., resistance triggered by adopter- and situation-specific factors such as an inclination to resist change and/or status-quo satisfaction) (Ram & Sheth 1989; Talke & Heidenreich 2014). *Active resistance* is caused by the characteristics of an innovation and represents the deliberate and conscious form of resistance that relates to awareness, consideration and active rejection (Klonglan & Coward 1970; Ram & Sheth 1989; Talke & Heidenreich 2014). In order to shed light on the constructed beliefs with respect to IA, active resistance is particularly interesting as it is driven by those factors that emerge when people consciously evaluate an adoption. Unlike the aforementioned drivers of passive resistance, these factors are triggered by the innovation itself and, if known, may help companies in reducing possible resistance. In order to shed light on active resistance, it is thus crucial to uncover its precursors, the inhibiting factors and their potential interaction with the enabling factors (Cenfetelli 2004; Cenfetelli & Schwarz 2011).

With the advent of radically new technologies, recent research in innovation and IS has increasingly relied on a dual-factored perspective to technology resistance, emphasising the importance of analysing the interplay of enablers and inhibitors (e.g., Chouk & Mani 2019; Henderson, Bradford & Kotb 2016; Polites, Karahanna & Seligman 2017). Cenfetelli (2004, p. 475) defines enablers as beliefs regarding a technology that "either encourage or discourage usage, dependent on valence", whereas inhibitors are defined as the technology-specific "perceptions held by a user about a system's attributes with consequent effects on a decision to use a system. They act solely to discourage use". Moreover, and based on Herzberg's (1966) dual-factor theory, Cenfetelli (2004) describes inhibitors and enablers as by no means being opposite constructs but rather dual-factored ones. Drawing from Lewin's (1947) model of opposing forces, Cenfetelli (2004) outlines the role of inhibitors and enablers in the context of technology resistance and proposes three main assumptions: (1) some perceptions solely discourage technology usage and drive resistance (inhibitors) and are qualitatively different from the opposite of those that drive usage intentions (enablers); (2) inhibitors and enablers are independent and can co-exist; and, most importantly, (3) inhibitors and enablers have different and asymmetric antecedents and consequences. Thus, similarly to Baumeister's (2001) "bad is stronger than good" or Kahneman and Tversky's (1979) "losses loom larger than gains", inhibitors can potentially override enablers. They are powerful and may have a direct effect on adoption intentions as well as an indirect effect mediated through enablers.

Study 1: Exploration of Mental Models

Study 1 is exploratory in nature and seeks to uncover the mechanisms underlying active resistance to IA. We use mental models, a lens often used to study perceptions or understandings about an IT artefact (e.g., Vandenbosch & Higgins 1996; Wells, Fuerst & Palmer 2017), to comprehensively explore the enablers and inhibitors that are deeply rooted in people's cognitive structures.

Design and Method

Mental models represent constructed small-scale models of external reality that essentially guide human reasoning and decision-making (Bagozzi & Lee 1999; Carley & Palmquist 1992; Craik 1967). There is consensus in the existing literature that the structural components in mental models occur in the form of more or less abstract visual images (Johnson-Laird & Byrne 2002; Zaltman & Coulter 1995). Zaltman & Coulter (1995) suggest that metaphors are the key to gaining access to these thought components. In order to elicit and interpret these metaphors, research may thus apply projective research techniques which use collages of photographs, pictures, drawings or artwork (Belk, Ger & Askegaard 2003; Zaltman & Coulter 1995). In doing so, each picture is treated as a metaphor that carries essential meanings about the object of investigation (Kunda 2002). Generally, this approach allows researchers to evoke perspectives and ideas that people would otherwise be unwilling or unable to communicate (Haire 1950). Furthermore, compared to other qualitative methods the use of projective techniques allows people to express themselves more directly, thoroughly and accurately (Levy 1985). Hence, in Study 1, we explore mental models with regard to IA using a projective technique (collage construction), followed by qualitative in-depth interviews.

Procedure

The sampling technique applied in the search for interview participants was based on a small non-probability, purposeful sample (Teddlie & Yu 2007). This is an adequate approach when searching for participants "who have experienced the central phenomenon or the key concept being explored" (Creswell & Plano Clark 2018 p. 173). As the aim of our qualitative study is not to generalise from our data but rather to generate in-depth insights that form the basis of our quantitative study, a sample size of around 10 participants is adequate (Creswell & Plano Clark 2018). We approached non-adopters of IA among whom we subsequently identified 10 persons who had previously actively resisted IA (age: M = 31.7 years; SD = 14.9; gender: 70% female). All identified persons had indicated that they had previously thought about buying an IA, but had deliberately refrained from doing so.

The study was conducted in a controlled laboratory setting and all participants took part voluntarily. For the collage construction, participants were provided with an internet-connected computer with Microsoft PowerPoint installed. This gave participants access to a large variety of images as input materials. The instructions were kept to a minimum in order to obtain a comprehensive overview of consumers' mental models of IA, to minimise trigger effects with respect to e.g. brand-related aspects, and to remove any kind of bias (please refer to the Appendix1 for further details). In the interviews that followed the collage exercise, participants were first asked some general questions about their considerations and attitudes regarding IA. Next, they were asked to describe their collages and the selected pictures in detail, including a description of the connections between the pictures as well as the narratives and rationales underlying each picture. To capture the deeper meaning of the pictures and to categorise them as inhibitors or enablers, the interviewer asked three central questions about each picture (Appendix 1). In addition to these main questions, a laddering approach following a pre-defined questionnaire was used to obtain detailed information and to reveal the origins and fundamental underlying values of each picture (Grunert & Grunert 1995). In a final step, participants were given the opportunity to re-arrange their collages, create meaningful clusters of pictures and draw links between them.

Data Coding and Analysis

In total, 10 collages and interviews were analysed (collage construction time: M = 34.5 min; SD = 15.6; interview length: M = 34.1 min; SD = 6.9). Figure 1 shows sample collages of two participants. Both the interview transcripts and collages were assessed in the analysis. All interviews were recorded digitally and fully transcribed. As proposed by Creswell & Plano Clark (2018), computer-assisted qualitative data analysis software (NVivo 11) was used for the content analysis. For the derivation of the consensus mental model, we pursued two main stages as suggested by Zaltman & Coulter (1995). That is, 1) identification of key themes; and 2) construction of the consensus mental model.

In stage 1, we used a theory-led approach for initial coding based on Cenfetelli (2004) where we assigned text codes (originator codes) to the following two major categories: inhibitors (uniquely driving resistance, 106 text codes) or enablers (either encouraging or discouraging acceptance, dependent on valence, 75 text codes) (see Question 3 in Appendix 1: If interview statement/picture combinations were negatively connoted, they were coded to the inhibitor category and vice versa). Within these two categories, in a second step, we coded overarching themes (connector and destination constructs) (Zaltman & Coulter 1995). In a third step, four coders independently assigned the originator codes to these overarching themes and also coded logical links in-between based on the interview storytelling, yielding a substantial inter-rater agreement reflected by a Cohen's Kappa of 0.72 (Cohen 1960). In the last step, diverging views were discussed and contextualised with extant theory (e.g., the theoretical definitions and predictors of perceived usefulness and ease of use by Davis (1989) and Venkatesh (2000)). The resulting coding scheme consisted of 11 enabler and 12 inhibitor constructs (see Appendix 2).

In stage 2, we followed the idea of the "three mosts" in order to generate an aggregated consensus mental model (Zaltman & Coulter 1995). That is, for inclusion in the mental model, we considered only those constructs that were "most thought by most people most of the time" (Zaltman & Coulter 1995 p. 44). The cut-off for inclusion in the consensus mental model were aspects that were mentioned by at least 50% of the participants. Thus, less salient aspects were dropped. Moreover, we used a centrality measure *C* to reveal how central the constructs are to the mental model. *C* reflects the ratio between the sum of direct logical links between an originator code and a destination construct and the total number of logical links in the mental model (Yan & Ding 2009). Figure 2 depicts the derived consensus mental model.

Figure 1. Mental model collages of two participants

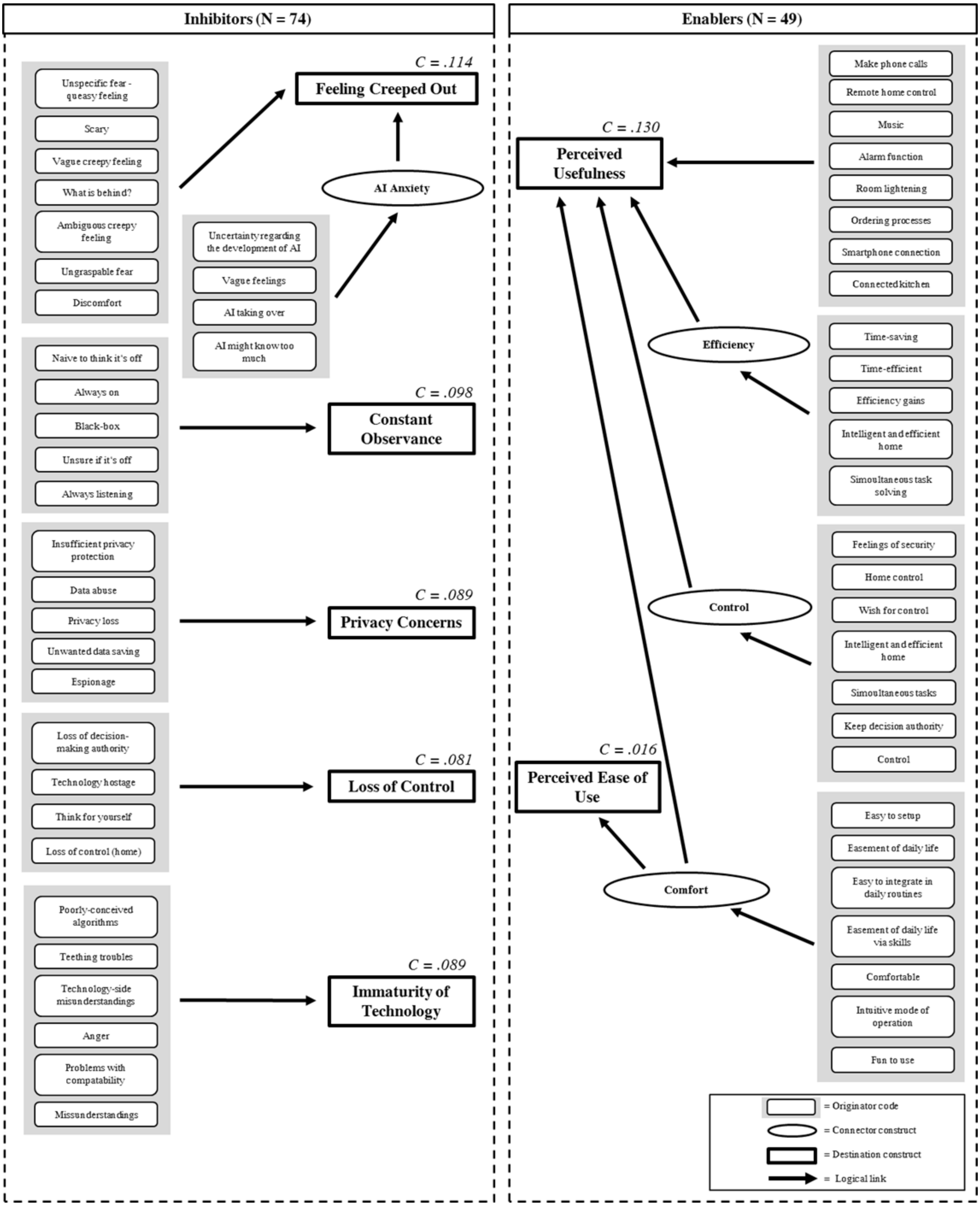


Figure 2. Consensus mental model

Table 1. Description of the identified inhibitor and enabler constructs

Construct	Description
Feeling Creeped Out	Anxiety aroused by the ambiguity of whether or not there is something to fear from IA and/or the ambiguity of the precise nature of the threat that IA might present.
Constant Observance	Doubts about whether IA are actually turned-off and at what time they are recording.
Privacy Concerns	Concerns about whether uniquely identifiable data is collected, stored and used.
Loss of Control	A perceived loss of control or disempowerment of one's home.
Immaturity of Technology	Expected immaturity of technology that may lead to malfunction.
Perceived Usefulness	The degree to which a person believes that using IA would provide practical features as well as enhance his or her efficiency, control and comfort throughout daily life.
Perceived Ease of Use	The degree to which a person believes that using IA would be easy to set up and integrate into daily routines.

Descriptive Mental Model Findings

The final consensus mental model consists of seven destination constructs (five inhibitors and two enablers) that are composed of four connector and multiple originator codes within the two main categories of inhibitors and enablers. The centrality measures reveal that the enabler *perceived usefulness* (*C* = .130) and the inhibitor *feeling creeped out* (*C* = .114) have the highest centrality in the consensus mental model. Overall, the centrality measure indicates a hierarchical structure along with the relative importance of the beliefs in non-users' mental models. An overview of all inhibitors and enablers as well as a short description based on the verbatim interviews and extant literature can be found in Table 1 (an overview of the full set of inhibitors and selected example quotes as well as all final collages are provided in the Appendices 3 & 4).

Emergent Conceptual Model

Although our participants had decided against IA in the past, they still held some positive beliefs with respect to the *ease of use* and overall *usefulness* of IA. They reported, for example, that they consider IA to be easy to set up and expect an intuitive operation. Moreover, some participants anticipated that IA would be fun to use. These beliefs correspond with the *perceived enjoyment* identified by Venkatesh (2000) as an important facet of perceived ease of use. Furthermore, many participants expected IA to be generally *useful* in several respects (e.g., to play music or to control the smart home) and expected an overall increase in *efficiency*, *control* and *comfort* in their daily lives.

Previous research in the context of smart objects has reported significant positive effects of perceived usefulness and perceived ease of use on attitude and intention to use (Kim & Shin 2015). Furthermore, the enabling effects of perceived usefulness and ease of use have previously been demonstrated in resistance studies (e.g., Bhattacherjee & Hikmet 2008; Guo et al. 2013). In sum, prior research has found both *perceived usefulness* and *perceived ease of use* to be positively related to IT usage intention. This leads us to hypothesise:

H1: *Perceived usefulness of IA is positively related to adoption intention.*

H2: *Perceived ease of use of IA is positively related to adoption intention.*

Resistance

The deliberate decision against IA that was voiced by our participants was the result of an active resistance that precluded acceptance. Generally, this negative relationship between resistance and acceptance (Nov & Ye, 2009) or intention to use (Bhattacherjee & Hikmet, 2007; Guo, Sun, Wang, Peng, & Yan, 2013; Hsieh & Lin, 2018) has been demonstrated in many studies. Overall, we thus hypothesise:

H3: *Resistance is negatively related to the intention to use IA.*

Resistance beliefs and inhibitors not only directly impact intention to use but can also have an indirect impact via enablers (Cenfetelli, 2004). For example, the presence of inhibitors, mental reservations and resistances may distort the perception of enablers and thus negatively influence usage intentions (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011). These distorting effects of inhibitors and resistance have already been the subject of previous empirical dual-factor-type resistance studies (Bhattacherjee & Hikmet, 2007, 2008; Guo et al., 2013). It can thus be expected that this relationship also holds true in our context, which leads us to the following hypotheses:

H4: *Resistance is negatively related to the enabler perceived usefulness.*

H5*: Resistance is negatively related to the enabler perceived ease of use.*

Feeling creeped out (C = .114)

The analysis of the interviews revealed that many participants reported an elusive and ambiguous feeling of threat detached from any clear-cut fear. One participant remarked: *It's just the creepy sensation that someone is listening, and I do not know who. However, I am not afraid that someone will find out something specific about me, such as my bank account number. I also do not feel like I'm saying anything that could be useful to someone* (no specific fear). *It's simply a queasy feeling.* Another participant stated: *It just feels as if there is a third person listening to you. A person that is somehow there but you cannot grasp. That feels scary to me*. A third participant explained: *It's not a concrete fear, it's more of a vague creepy feeling*, and another participant reported having *vague feelings* about AI*.* In addition, many participants used meaningful images in their collages, such as creepy-looking skull-headed cyborgs or masked persons. Masks usually hide the true emotions and intentions of the person wearing them and are thus a major trigger of vagueness, uncertainty and ambiguity (Watt, Maitland & Gallagher 2017; Honigmann 1977). The vagueness of "what's underneath" is also reflected in the following statement of one participant: *The device is able to literally speak with you and I try to imagine what's behind it*.

These findings suggest that IA, despite their potential benefits, may be associated with an aura of creepiness. Interestingly, the notion of creepiness has recently begun to garner attention in fields such as psychology, marketing and HCI (e.g., Kirk, Peck & Swain 2018; Langer, König & Fitili 2018; McAndrew & Koehnke 2016; Ostrom, Fotheringham & Bitner 2019). For instance, a recent study by Tene & Polonetsky (2015) suggests that the sometimes non-transparent nature of novel technologies may grate existing social norms and may thus lead to perceptions of creepiness on the part of consumers. In a similar vein, studies on the "Uncanny Valley" effect argue that artificial beings that imperfectly resemble human beings are considered eerie and creepy (Mori, MacDorman & Kageki 2012).

Note, however, that the Uncanny Valley effect refers to the appearance of human-like technologies such as humanoid robots. In contrast, our participants referred to vague and ambiguous feelings of threat associated with the use of IA. This view of creepiness is more in line with the conceptualization of McAndrew & Koehnke (2016) who define creepiness as the "anxiety aroused by the ambiguity of whether there is something to fear or not and/or by the ambiguity of the precise nature of the threat that might be present" (p. 10). The authors claim that every person has a built-in creepiness detector that helps them keep their distance from creepy and suspicious people.

Importantly, Neff (2018) argues that this creepiness detector may extend beyond social contexts and may also be active when people are confronted with intelligent technologies. For instance, when interacting with a smart household device, people may project emotions on the device and may rely on social norms for evaluating the device's actions. In addition, Wuenderlich & Paluch (2017) found that people are less and less able to distinguish whether they are interacting with a human or a service bot. In sum, these findings suggest that interpersonal aspects such as "feeling creeped out" may also emerge in interactions with technologies. This notion is also supported by the statements of some of our interview participants who spoke about a "person" in the room and the "humanisation" of technology.

Hence, similar to social contexts where a built-in creepiness detector warns people to keep away from creepy persons that may or may not pose a threat, this detector may also be activated in technology contexts, warning us to stay away from creepy technologies. In light of these arguments, we propose that perceptions of creepiness are an important and novel inhibitor to the adoption of AI-empowered household technologies. We thus hypothesise:

H6: *Feeling creeped out is positively related to resistance to IA.*

Constant observance (C = 0.098)

This inhibitor expresses the doubt of not knowing if and when IA are actually switched off or when they are recording. One interviewee stated: *If the device is in the same room with me, I would be naive enough to think that it only records me if I directly address it but never if I don't.* Other comments were: *I do not trust that the product is really off*; or, *I think they are always on*.

Much like the previously discussed aspect of feeling creeped out, constant observance appears to represent a hitherto unexplored aspect. Berinato (2014) relates to this aspect, describing the general issue of not receiving notifications or requests from a smart device when it is switched on. Moreover, Kummer, Recker & Bick (2017) introduce "surveillance anxiety", which relates to the negative feelings of being under constant surveillance. It describes the fear that somebody might be watching one's mistakes or the feeling of being permanently *monitored*. The concerns voiced by our participants, in contrast, were more "primary" in that they referred to not knowing *when* or *if* the device is actually switched on. One participant drew an interesting comparison: *This uncertainty of when or whether the device is on or off stems from my own experience with smartphones. I once spoke to friends about something and then got related suggestions on my smartphone. This implies that my cell phone had been listening or was kind of switched on even though I had not actively requested it.* Taken together, we suggest that this construct represents a further novel candidate for being an inhibitor to AI-empowered household technology. We thus hypothesise:

H7: *Constant observance is positively related to resistance to IA.*

Privacy concerns (C = .089)

Privacy concerns were frequently mentioned by our interviewees. One participant stated: *One does not know exactly who is behind it and has access to the data*; at the same time, another reported: *Being spied on by the manufacturer describes best what I feel with respect to these devices*. A third participant simply feared an unpleasant invasion of privacy through the use of IA. In the collages, participants depicted these aspects by an ear attached to a smartphone or an eye peeking through a keyhole. Another participant stressed that IA may result in a negative privacy calculus: *They are just a gimmick that would make me think twice about whether it's worth losing data sovereignty*. In general, data privacy concerns have been a major resistance factor since the advent of the Internet and a wide range of articles in IS research are devoted to the subject (Bélanger & Crossler 2011). Various studies have shown the inhibiting effects of privacy concerns or linked privacy calculus considerations with (smart) technology adoption (e.g., Kehr et al. 2015; Sheng, Fiona Fui-Hoon Nah & and Keng Siau 2008). With the advancement of technology in the domains of AI, smart objects and the IoT, potential privacy-related vulnerabilities are getting more and more attention (e.g., Hoehle et al. 2018; Lowry, Dinev & Willison 2017). We thus hypothesise:

H8: *Privacy concerns are positively related to resistance to IA.*

Loss of control (C = .081)

Perceived *loss of control* emerged as an important inhibiting aspect in the context of IA. Participants' doubts in this category range from a simple loss of decision-making autonomy (*fear of what the system does when you're away from home*) to the idea of becoming hostage to one's own technology within one's home. One participant illustrated this aspect in the collage by using an expressive picture portraying a prison corridor. Another interviewee remarked: *One might become a hostage to technology, it's the most negative association I have with respect to IA*. These findings are in line with recent research on perceived disempowerment and loss of control in the context of innovations (e.g., Faraji-Rad, Melumad & Johar 2017) and innovative technologies (Bhattacherjee & Hikmet 2008; Heiskanen et al. 2007; Schweitzer & van den Hende 2016). Bhattacherjee & Hikmet (2008), for instance, showed that perceived loss of control is a major inhibitor to the adoption of healthcare information technology (HIT) among physicians. Moreover, Schweitzer and van den Hende (2016) found that individuals associate smart objects with feelings of disempowerment and demonstrated that this negatively affects adoption intention. In the same vein, Heiskanen et al. (2007) found that loss of control represents a major resistance factor to smart home products. We thus hypothesise:

H9**:** *Perceived loss of control is positively related to resistance to IA.*

Immaturity of technology (C = .089)

Finally, our participants stated that *immaturity of technology* was one of the reasons preventing them from using IA. One participant portrayed the possible frustration caused by immature technology using a meaningful picture showing a person smashing a laptop with a baseball bat. Another participant said: *Many teething troubles, which goes hand in hand with difficulties regarding compatibility and integration with other products*. Furthermore, participants expected poorly-conceived algorithms or indicated an unwillingness to invest in a system when the technology is not mature. Previous research has described this aspect as a *functional barrier* to innovation adoption (Ram & Sheth 1989). More recent research by Joachim, Spieth & Heidenreich (2018) and Talke and Heidenreich (2014) found that consumers' fear that a product could be dysfunctional or malfunctional represents the most significant obstacle to adopt innovations across a variety of product contexts (e.g., a smart dusting robot). Based on our findings and previous literature, we thus hypothesise:

H10: *Immaturity of technology is positively related to resistance to IA.*

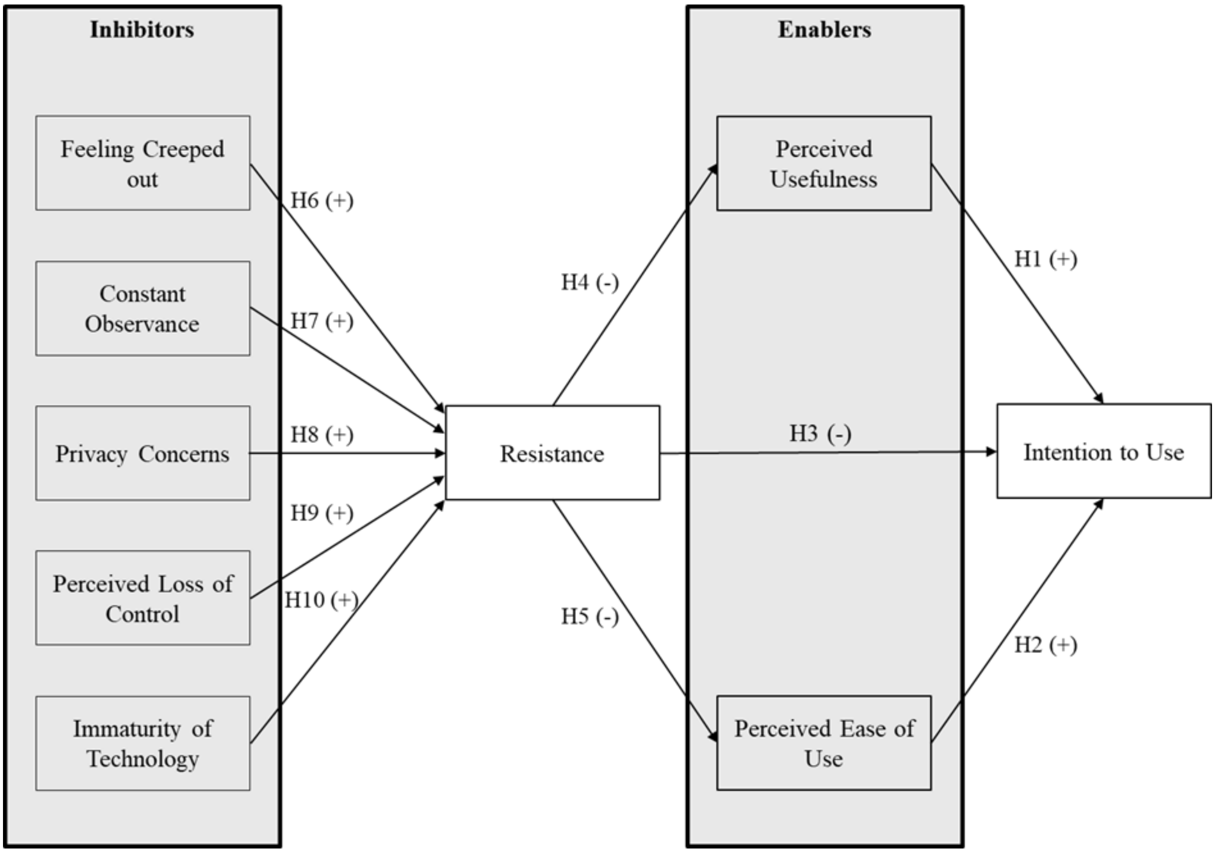


Figure 3. Hypothesised research model

Study 2: Testing the Emergent Research Model

The findings from Study 1 inform Study 2 (Ågerfalk 2013; Venkatesh, Brown & Bala 2013). In Study 2, we aim to test our hypothesised relationships with current non-adopters to quantitatively test their sturdiness and generalisability (Creswell & Plano Clark 2018; Venkatesh, Brown & Bala 2013; Walsh 2015). In doing so, we seek to elucidate the nomological network underlying our hypothesised relationships (Creswell & Plano Clark 2018).

Research Design, Participants and Measurements

We developed a survey that was pre-tested in multiple rounds of refinement with pre-test participants and other academics. Whenever possible, we used or adapted existing measurement constructs (see Table 2). Given the absence of pre-validated scales for *feeling creeped out* and *constant observance*, we created our own multi-item measures based on the rich interview verbatim from Study 1. This measurement development was inspired by the steps proposed by Nunnally & Bernstein's (1994) domain sampling technique which has been applied in previous IS studies (e.g., Bhattacherjee & Hikmet 2007). First, we developed a conceptual definition for each of the constructs, describing the overall domain of content. For example, our conceptual definition for *feeling creeped out* was inspired by McAndrew & Koehnke's (2016) definition of creepiness. Second, we selected candidate items from the interviews to adequately represent this domain. We created a four-item scale for *feeling creeped out* and a three-item scale for *constant observance*.

We pursued a random probabilistic sampling, including a sufficiently large number of participants to ensure the results' representativeness (Creswell & Plano Clark 2018). We recruited 409 non-adopters using the online survey platform Amazon MTurk (age: M = 34.71 years; SD = 12.03; gender: 57% female). To ensure that the survey participants were non-adopters, we integrated filter questions asking whether they currently owned or used IA. Afterwards, participants were asked to complete the survey including the constructs from our research model.

Table 2. Measurement items

Construct and reference	**CA**	**Item-#**	**Items**[1]
Constant Observance (CO) Own scale derived on the basis of domain sorting (Nunnally & Bernstein 1994)	.814	CO1	I would not be sure when the intelligent assistant is turned on or off.
		CO2	I do not know whether the intelligent assistant could be switched on or off.
		CO3	I do believe that the intelligent assistant is eavesdropping at any time.
Feeling creeped out (FC) Own scale derived on the basis of domain sorting (Nunnally & Bernstein 1994)	.886	FS1	An intelligent assistant is giving me a creepy feeling of another person being in the room.
		FS2	Having an intelligent assistant in my room would creep me out.
		FS3	It feels creepy that someone could know more about myself than me.
		FS4	An intelligent assistant is comparable to an invisible guest in my home.
Intention to Use (IU) Based on Venkatesh & Davis (2000)	.946	IU1	Assuming I have access to an intelligent assistant, I intend to use it.
		IU2	Given that I have access to an intelligent assistant, I predict I would use it.
Immaturity of Technology (IT) Based on Talke & Heidenreich (2014) and Joachim, Spieth & Heidenreich (2018)	.901	IT1	I have some doubts about the product's reliability.
		IT2	I am doubtful whether or not the product will work as advertised.
		IT3	I question the advertised functions of the product.
Perceived Ease of Use (PEOU) Based on Davis (1989)	.913	PEOU1	Learning to operate an intelligent assistant would be easy for me.
		PEOU2	I would find it easy to get the intelligent assistant to do what I want it to do.
		PEOU3	My interaction with an intelligent assistant would be clear and understandable.
		PEOU4	I would find an intelligent assistant to be flexible to interact with.
Perceived Usefulness (PU) Based on Davis (1989)	.956	PU1	Using an intelligent assistant will improve my performance.
		PU2	Using an intelligent assistant will increase my productivity.
		PU3	Using an intelligent assistant will make me more effective.
		PU4	Overall, I find an intelligent assistant to be useful.

Table 2. *(Continued)*

Construct and reference	CA	Item-#	Items[1]
Privacy Concerns (PC) Based on Lwin, Wirtz & Williams (2007) *(7-point Likert-scale ranging from 1 = not at all concerned to 7 = extremely concerned)*	.915	PC1	How concerned are you that your personal data may be used for purposes other than the reason you provided the information for?
		PC2	How concerned are you about your personal privacy using an intelligent assistant?
		PC3	How concerned are you about the fact that an intelligent assistant might know/track the sites you visited?
		PC4	How concerned are you about intelligent assistant's sharing your personal information with other parties?
Resistance (RES) Based on (Mani & Chouk 2018; Mani & Chouk 2017)	.893	RES1	I am likely to be opposed to the purchase of an intelligent assistant.
		RES2	I am likely to be opposed to the discourses extolling the benefits of an intelligent assistant.
		RES3	An intelligent assistant is not for me.
Perceived Loss of Control (PLC) Based on Schweitzer & van den Hende (2016)	.893	PLOC1	An intelligent assistant takes decisions that I would prefer to make myself.
		PLOC2	I fear that an intelligent assistant could take actions that I dislike.
		PLOC3	An intelligent assistant reduces my possibilities to decide which product I want to buy.
		PLOC4	An intelligent assistant reduces my freedom of action.

[1]*Unless otherwise stated, we used a 7-point Likert-scale (1 = strongly disagree to 7 = strongly agree)*

Analysis

For the statistical analysis, we opted for structural equation modelling and used variance-based partial least squares (PLS) and the SmartPLS 3.0 software tool (Hair, Ringle & Sarstedt 2011). Because our research model included constructs that we developed on our own, PLS with its relaxed standards is well suited (Hair, Ringle & Sarstedt 2011; Reinartz, Haenlein & Henseler 2009). The analysis was performed using the testing schema proposed by Fornell & Larcker (1981). We first evaluated the overall measurement model and then assessed the structural model and the hypothesised paths.

Measurement Model and Overall Model Fit

The reliability of our measurement model was evaluated via the items' composite reliability (CR) and average variance extracted (AVE) (Fornell & Larcker 1981). As shown in Table 3, the composite reliabilities and the average variance extracted range above the suggested cut-off values of .70 and .50, respectively (Fornell & Larcker 1981; Hsu & Lin 2008). In addition, all measures demonstrated a satisfactory convergent validity with standardised item loadings exceeding .70 (Chin 1998). All item loadings were significant and greater than .70, indicating a good convergent validity of the constructs. As shown in Table 4, our constructs showed a good discriminant validity as all correlations in our sample were significantly lower than the square roots of our AVEs (Fornell & Larcker 1981).

Table 3. Reliability and convergent validity

	CR	AVE	ITEM	Loading
Constant Observance (CO)	.891	.731	CO1	0.910
			CO2	0.860
			CO3	0.792
Feeling Creeped Out (FC)	.974	.949	FS1	0.914
			FS2	0.880
			FS3	0.800
			FS4	0.857
Intention to Use (IU)	.938	.834	IU1	0.974
			IU2	0.974
Immaturity of Technology (IT)	.927	.680	IT1	0.902
			IT2	0.914
			IT3	0.924
Perceived Ease of Use (PEOU)	.934	.826	PEOU1	0.751
			PEOU2	0.867
			PEOU3	0.851
			PEOU4	0.838
			PEOU5	0.805
			PEOU6	0.831
Perceived Usefulness (PU)	.968	.883	PU1	0.948
			PU2	0.949
			PU3	0.951
			PU4	0.910
Privacy Concerns (PC)	.907	.710	PC1	0.910
			PC2	0.921
			PC3	0.838
			PC4	0.903

Table 3. *(Continued)*

Resistance (RES)	.941	.798	RES1	0.928
			RES2	0.878
			RES3	0.915
Perceived Loss of Control (PLC)	.933	.823	PLOC1	0.863
			PLOC2	0.809
			PLOC3	0.824
			PLOC4	0.872

Table 4. Discriminant validity

	CO	FC	IU	IT	PEOU	PU	PC	RES	PLC
CO	**.855**								
FC	.566	**.864**							
IU	-.275	-.335	**.974**						
IT	.392	.427	-.227	**.913**					
PEOU	-.107	-.231	.358	-.253	**.825**				
PU	-.212	-.156	.722	-.168	.335	**.776**			
PC	.452	.570	-.279	.513	-.209	-.191	**.842**		
RES	.572	.545	-.328	.419	-.103	-.377	.429	**.894**	
PLC	.420	.523	-.630	.413	-.225	-.618	.541	.453	**.907**

The diagonal of the table represent the average variance extracted (AVE)

Test of the Structural Model

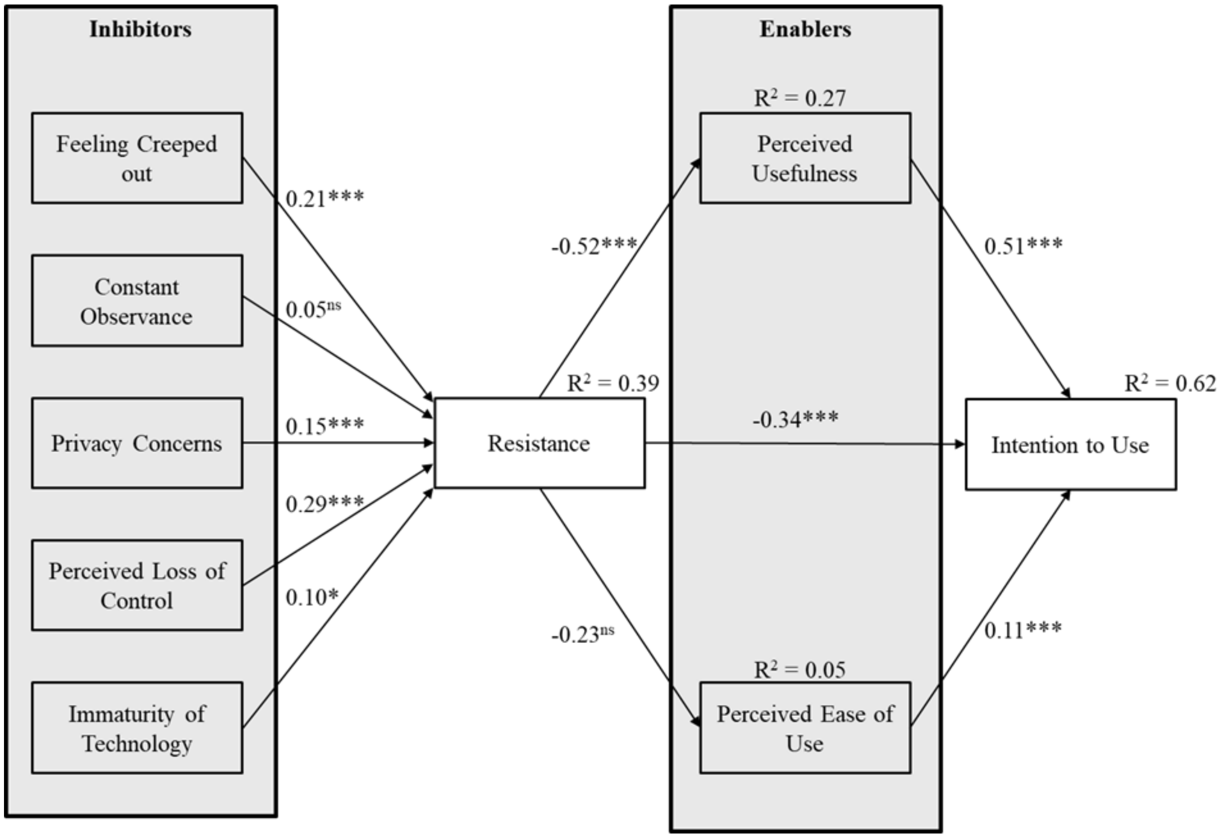
The construct reliabilities exceeded the generally accepted Cronbach's alpha threshold of .70 for all constructs (Nunnally & Bernstein 1994). Overall, the research model explained 62% of the variance in our main dependent variable *intention to use*, which can be considered substantial in IS research (Urbach & Ahlemann 2010). Furthermore, the variance explained in the constructs *perceived usefulness*, *perceived ease of use* and *resistance* was 27%, 5% and 39%, respectively. Overall, our statistical analysis supported most of our hypotheses. When looking at individual path coefficients, we found that seven hypothesised paths from our research model were significant at $p < .01$, one path was significant at $p < .1$ and two were non-significant. The directionality of the different significant paths was as predicted (see Figure 4).

The *intention to use* IA was predicted positively by perceived usefulness ($ß = .51$; $p < .01$) and *perceived ease of use* ($ß = .11$; $p < .01$), as well as negatively by *resistance* ($ß = -.34$; $p < .01$), providing empirical support for hypotheses H1, H2 and H3, respectively. Moreover, the effect of these findings supports the notion that intention to use is predicted by the interplay of both enabling and inhibiting factors.

Moreover, *resistance* has a significant negative effect on *perceived usefulness* (*ß* = **-**.34; *p* < .01), but no effect on *perceived ease of use* (n.s.), thus providing support for H4 but not for H5. Hence, it appears that resistance distorts *perceived usefulness* much more than *perceived ease of use*. It is noteworthy that the extent of the direct effect of *resistance* on *perceived usefulness* (*ß* = **-**.52) is greater than its direct effect on *intention to use* (*ß* = **-**.34), which supports the biasing effect of inhibitors on enablers.

Regarding the specific inhibitors that were identified in Study 1, *feeling creeped out* had a significant positive effect on *resistance* (*ß* = .21; *p* < .01), thus supporting H6, whereas we had to reject H7 as the construct *constant observance* had no effect (n.s.). The further inhibiting constructs tested also showed significant positive effects on *resistance*, which supports H8–H10 (*privacy concerns*: *ß* = .15, *p* < .01; *perceived loss of control*: *ß* = .29, *p* < .01*; immaturity of technology*: *ß* = .10, *p* < .1).

As mentioned previously, the inhibitors accounted for 39% of the variance in *resistance.* This provides initial support for the importance of these inhibitors in shaping non-adopters' resistance to IA (Urbach & Ahlemann 2010). Obviously, however, there remains some residual variance suggesting that there are further important predictors that have not been included in our model. Nevertheless, our model explains a large part of the variance in the dependent variables and supports most of the derived hypotheses.



*Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1, ns = p > 0.1*

Figure 4. Statistical analysis of hypothesised research model

Discussion

The aim of Study 2 was to reveal the nomological paths underlying the resistance to IA. Except for the inhibitor *constant observance,* all inhibitors had a significant impact on *resistance*. Remarkably, *feeling creeped out* had the second-largest effect among the inhibitors tested, thus supporting its significance with respect to resistance to IA. Referring to McAndrew & Koehnke (2016), our findings thus suggest that people's creepiness detectors are active not only in social contexts but also in technological ones.

Overall Discussion, Contributions and Limitations

In this study, we chose a comprehensive mixed-methods approach to investigate the phenomenon of resistance to IA. Our results show that the phenomenon is diverse and multifaceted. Overall, our study contributes to extant IS research in three ways:

First, we examined the belief structures and conceptions of people who actively resisted IA. This allowed us to explore a consensus mental model that includes a comprehensive set of inhibitors to IA. In doing so, our findings show that when studying resistance in the context of AI-empowered technologies, new theoretical constructs driving people's actions may come into play. Alongside traditional inhibitors such as privacy and control-related fears, we identified novel technology-specific inhibitors such as feeling creeped out and constant observance. In the past, research and practice have greatly benefitted from such discovery of technology-specific inhibitors across different contexts such as perceived identity threat in the context of digital technologies in the workplace (Craig, Thatcher & Grover 2019) or switching costs and security concerns in the context of cloud migration (Bhattacherjee & Park 2014).

Second, this study adds to the literature by integrating and combining different theoretical strands within resistance theory such as *active innovation resistance* (e.g., Ram & Sheth 1989) and the *dual-factor model of technology resistance* (e.g., Cenfetelli 2004). This theoretical underpinning allowed us to comprehensively explain the underlying mechanisms of resistance to IA and at the same time proposes a novel, more holistic lens in the study of technology acceptance.

Third, on a more superordinate level, our research follows the call to apply new research methods in the IS domain by introducing an approach that allows us to gather rich mental model data using creative collages (Ågerfalk 2013; Te'eni et al. 2015). This approach offers a way to explore people's cognitive structures that, to the best of our knowledge, has not yet been applied in IS research. Furthermore, we counter the trend of current IS research to approach new digital technologies exclusively from the perspective of *technology as a solution* by taking a more critical perspective in the sense of *technology as a cause of problems* (Rowe 2018).

In addition, our research contributes to practice. Besides improving the general understanding of individuals' mistrust and resistance behaviour, the identified inhibitors have specific implications for technology design (Cenfetelli & Schwarz 2011). Since the identified inhibitors explain why people decide against IA once they deliberately think about it, these new insights can be used in practice as potential starting points to reduce resistance and stimulate the diffusion of IA.

Looking ahead, the finding that some people are prone to feel creeped out by IA is an aspect that will likely become increasingly relevant and may fuel future research on AI-empowered technology at large (e.g., AI in digital service encounters, see Ostrom, Fotheringham & Bitner (2019)). Future research may, for example, investigate the specific technological features that trigger perceptions of creepiness. In social contexts, *unusual behaviour* or *physical appearance*, as well as some *occupations* (e.g., clowns) or *hobbies* (e.g., collecting dolls or insects), have been shown to be predictors of creepiness (McAndrew & Koehnke 2016). In the same vein, practice might benefit from specific insights regarding the technological characteristics that fuel creepiness which can be used as a starting point to reduce resistance.

Finally, our findings should be interpreted in light of their limitations. First, the analysis and coding of Study 1 might be subject to researcher bias and personal interpretations of the coders which, however, is common in qualitatively-driven constructivist research (Onwuegbuzie & Leech 2007). In Study 2, we had to create new scales for feeling creeped out and constant observance which is a common approach in exploratory settings. However, as these scales were created for the context of IA, they may not generalize to other technology contexts. Thus, an accurate scale development procedure for a more general construct of feeling creeped out should be subject to future research. Lastly, given that our data collection was performed in Germany, we are aware that the generalisability of our findings might be also limited due to the cultural setting which may differ from others in terms of cultural beliefs (Hofstede 2011).

Conclusion

Intelligent assistants are a major breakthrough in the digitisation of our daily lives. Empowered by increasingly powerful IT and remotely operated via voice control, they give rise to myriads of opportunities but also to novel threats. Our objective was to shed light on the "dark side" and understand the mechanisms and drivers underlying active resistance to IA. In summary, we assessed the as-of-yet underdeveloped topic of resistance in the context of IA using a mixed-methods research approach. Our research exposed novel inhibitors that are specific to technologies empowered by AI. In particular, the aspect *feeling creeped out* represents a promising factor that could both stimulate fruitful discussions and form the basis for further research on AI-empowered consumer technologies at large.

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Appendix Essay II

Appendix 1. Instructions to the participants of the collaging

Participants received the following introduction from the researchers prior to the collaging:

> "*Please think of intelligent assistants such as Google Home or Amazon Echo. Please try to grasp every association, belief, feeling or idea that intuitively comes into your mind regarding these technologies, then try to find pictures that, in your opinion, best convey those and create a collage. You can use common online search engines to find these pictures. There is no right or wrong answer and no time limit."*

We used a semi-structured interview guide consisting of four parts and a total of 21 questions. The following three questions were asked with regard to each picture in order to grasp their deeper meaning and to categorise them into inhibitors or enablers:

1) *"What is the narrative behind the picture and why has it been chosen for the collage?"*
2) *"Where do you think it comes from, for instance, own experiences, commercials, or word of mouth?"*
3) *"Please state whether the picture is positively or negatively connoted."*

Appendix 2. Coding scheme

Enablers and Inhibitors to the Adoption of Intelligent Assistants*

Inhibitors	Enablers	Inhibitors†	Enablers
	Perceived Usefulness		**9%**
Feeling Creeped Out		**7%**	
	Efficiency		**7%**
Constant Observance		**7%**	
Privacy Concerns		**6%**	
Loss of Control		**6%**	
	Comfort		**6%**
	Control		**6%**
Immaturity of Technology		**5%**	
AI Anxiety		**5%**	
Specific Negative Consequences		5%	
Existential Insecurities		5%	
Lack of Perceived Benefits		4%	
Fear of manipulation		3%	
	Multi-Functionality		3%
	Fun and Entertaining		3%
	Human-like Interaction		3%
Fear of Cyber-Attacks		3%	
	Status Signalling		2%
	Compatibility		2%
	Futuristic Lifestyle		1%
	Brand		1%
Financial Barriers		1%	
Sum		**57%**	**43%**

** Inhibitors or enablers that were included in the consensus mental model are written in bold*

† *% distribution of all text codes*

Appendix 3. Elicited inhibitors to the adoption of IA

Inhibitors	**Selected example quotes**
Feeling Creeped Out	"It's a rather unpleasant feeling (…) I want to talk about everything that I want to talk about in my room without thinking that Amazon is listening to everything. It's just an unpleasant feeling." "It's just the creepy sensation that someone is listening, and I do not know who. However, I am not afraid that someone will find out something specific about me, such as my bank account number. I also do not feel like I'm saying anything that could be useful to someone. Only that there would someone listening without me knowing that." "It's simply a queasy feeling." "It's not a concrete fear, it's more of a vague creepy feeling."
Constant Observance	"If the device is in the same room with me, I would be naive enough to think that it records me only if I directly address it but not when I'm not addressing it." "I would not be sure when the product is switched on or off. I mean I would think that it would stay in stand-by-mode and would constantly collect data, even when I turn it off." "I don't know when it is switched on or off and also I don't even know if you can switch it on or off at all."
Privacy Concerns	"I suppose if there is a box in the room which is listening to me all the time, you don't have any privacy left. I found this picture which fits well to my feelings when I googled *spying*."
Loss of Control	"I wanted to express my concern that one can't be quite sure what the system does when you are not at home or if the system is faulty that you can't control something like that." "By loss of control, I mean that especially with regard to artificial intelligence you don't know in which direction such a device will develop."
Immaturity of Technology	"There are a lot of first versions in the market and I think there is still plenty of room for improvement." "It could be annoying if these devices would not work in a way you want them to function."
AI Anxiety	"Artificial intelligence is threatening." "It could be negative when they (IA) become too intelligent." "There are always these films where robots become independent, freak out and destroy everything."
Other Specific Negative Consequences	"These devices encourage convenience or laziness because you don't even have to do the simplest things by yourself anymore. That's why I think it's an unnecessary convenience." "Interpersonal relationships become more superficial." "I find all the functions of the product to be confusing." "These devices make us forget our environment."
Existential Insecurities	"I'm afraid of being replaced by technology one day." "Through these devices everything is accelerating and getting faster. Do I want that all to happen, do I need that?"

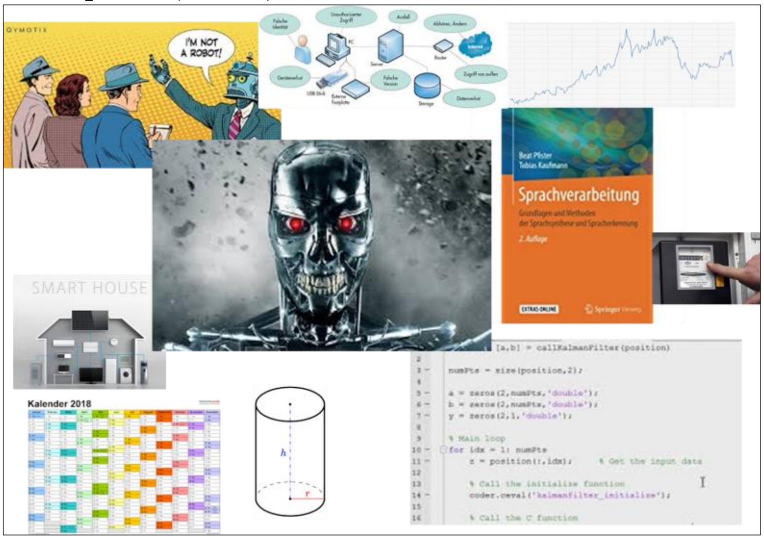
Appendix 3. (*Continued*)

Inhibitors	Selected example quotes
Lack of Perceived Benefits	"I do not see the added value." "I would not expect a lot from this system - like making my work easier or anything like that: It's more of a gimmick." "Here is something which is new, does it give me added value, does it help me? Of course, I think that it is efficient in a way, but couldn't I also do it on my own?"
Fear of Manipulation	"Based on the collected data you could get personalised online advertising, so this would be a discrete manipulation of the purchasing behaviour." "I am concerned about what a company could do with my data - e.g., performing specific price modifications or other negative changes which could impact me personally."
Fear of cyber-attacks	"I'm afraid of hackers (...) I know that there are still enormous security gaps." "Technically speaking, a data attack is possible, and there are individuals who could then exploit that." "You also have to consider that it is secured in an appropriate way and that it is protected from hackers."
Financial Barriers	"This kind of technology is expensive."

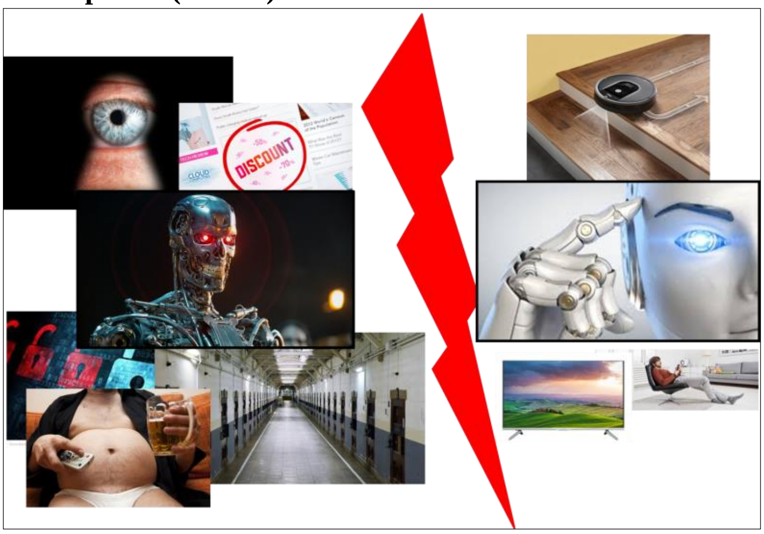
Appendix 4. Final collages and construction time per participant

Participant 1 (20 min)

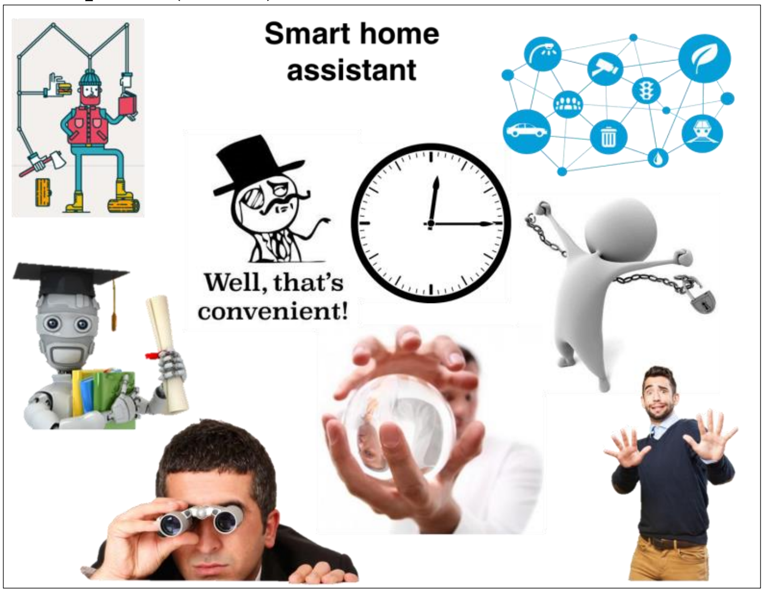
Participant 2 (21 min)



Participant 3 (19 min)

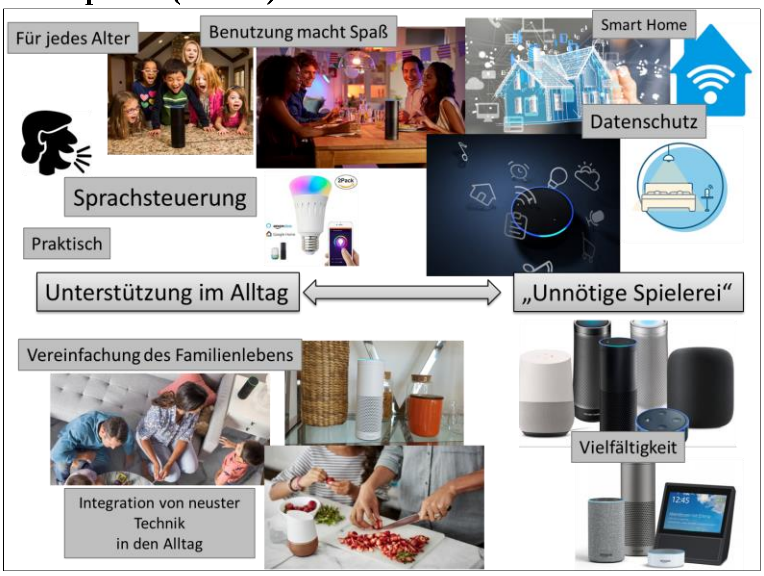


Participant 4 (36 min)



Participant 5 (60 min)

Participant 6 (57 min)

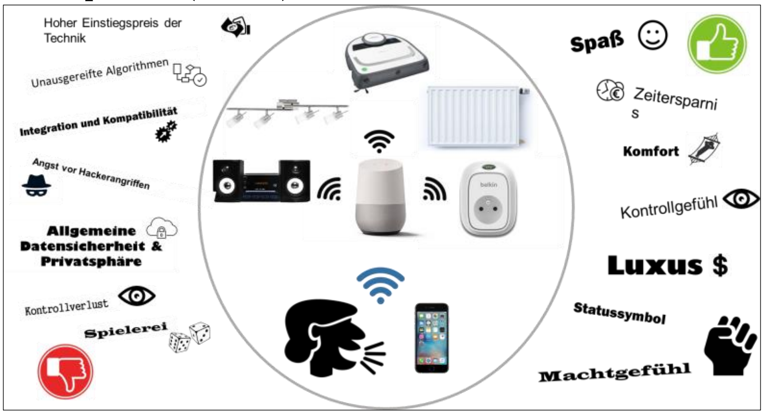


Participant 7 (26 min)

Participant 8 (28 min)

Participant 9 (28 min)

Participant 10 (50 min)



ESSAY III

Do Service Robots Harm Service Relationships? Examining the Effects of Robo-Advisors on Relationship Quality

Currently under review in the *Journal of Service Research* (*JSR*)

DO SERVICE ROBOTS HARM SERVICE RELATIONSHIPS? EXAMINING THE EFFECTS OF ROBO-ADVISORS ON RELATIONSHIP QUALITY

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Abstract

Professional service firms are increasingly replacing human advice by robo-advice in fields such as financial planning, medical consultation, or legal advice. In this research, we examine robo-advice from a relational perspective and argue that robo-advisors may undermine existing service relationships. Drawing on advice theory and social relationship theory, Studies 1 and 2 find that stand-alone robo-advisors harm relationship quality for those customers that have a communal relationship with their service provider compared to hybrid robo-advisors that also include a human advice layer. On the other hand, no such differences or even a reverse pattern of results were found for customers that had an exchange relationship with their service provider. Finally, Study 3 shows that robo-advisors that mimic human social support may backfire for customers with a communal relationship and may further decrease relationship quality compared to robo-advice without artificial social support. Again, no such effects were revealed for customers with an exchange relationship. These findings have important implications for service research and practice by showing that managers need to consider the relational implications associated with introducing robo-advisors and by demonstrating what managers can do to prevent that robo-advisors harm existing service relationships.

Keywords: *Robo-advice, relationship marketing, professional services, self-service technology*

Introduction

In recent years, professional service firms have started to introduce robo-advice, a self-service technology that provides personalized advice based on artificial intelligence (AI). Robo-advice is especially prominent in the financial services industry, in which renowned banks and brokers such as Bank of America, Santander, or Charles Schwab have launched robo-advisors that develop investment plans for customers (Jung et al. 2018). However, other professional service industries are also beginning to automate advice. For example, Dentons, one of the biggest US law firms, has invested in ROSS, a legal advisor app based on IBM Watson (Croft 2016). In China, the Guangzhou Second Provincial Central Hospital was one of the first to offer its patients health consultation and diagnosis through a chatbot (Huang 2018).

With AI rapidly progressing, one may expect that financial robo-advice and similar self-services (e.g., robo-doctors, robo-lawyers) will soon outperform professional service providers such as financial consultants or lawyers. Existing robo-advisors are already capable of developing complex recommendations based on the processing of large amounts of data and machine learning. Future generations of robo-advisors may even demonstrate intuitive and empathic intelligence when advising customers (Huang & Rust 2018). That is, robo-advisors may soon understand customers' emotions and provide socially supportive communication (Wirtz et al. 2018). Hence, scholars and practitioners alike have argued that robo-advisors will experience wide-spread adoption as they will not only increase service efficiency but may also deliver a better service to customers (Davenport, Libert & Beck 2018; Marinova et al. 2016).

While robo-advisors may replace humans in many services (Huang & Rust 2018), existing research has, to the best of our knowledge, rarely considered robo-advisors from a relational perspective (Jörling, Böhm & Paluch 2019; Mende 2017). That is, as professional service encounters are first and foremost social experiences characterized by a high degree of customer participation and interpersonal exchange (Chan, Yim & Lam 2010), the widespread implementation of robo-advisors may undermine the relationships between service providers and their customers. For instance, a study by Giebelhausen et al. (2014) found that technologies that detain customers from engaging in interpersonal exchange may reduce service encounter evaluations because customers are not able to experience pleasing social relations anymore. From this perspective, it is important to understand how customers evaluate the implementation of robo-advisors against the background of their existing service relationships and how robo-advisors affect the quality of these relationships.

In this research, we address this gap in the literature. First, we discuss how robo-advice differs from human advice and identify different types of robo-advice (i.e., robo-advisors that operate on a stand-alone basis or hybrid advisors that are combined with human advice, and robo-advisors with or without artificial social support). Second, drawing on social relationship theory (Clark & Mills 1993), we argue that customers have different kinds of relationships with service firms, ranging from exchange relationships that follow a transactional, quid pro quo logic to communal relationships characterized by mutual care and concern. Combining these streams of research, we develop a conceptual model that proposes that the extent to which different types of robo-advisors affect relationship quality depends on the kind of relationship that customers have with their service provider.

These propositions are tested through three experimental studies. Consistent with our conceptual framework, Studies 1 and 2 find that stand-alone robo-advisors negatively affect relationship quality for those customers that have a communal relationship with a service firm compared to hybrid robo-advisors. However, no such effects are evident for customers with an exchange relationship. Contrary to our predictions, Study 3 finds that combining robo-advice with artificial social support (i.e., a robo-advisor expressing empathy with a customer) backfires for customers with a communal relationship and may further decrease relationship quality compared to robo-advice without artificial social support. Again, no such effects were revealed for customers with an exchange relationship.

In examining how service relationships are affected by robo-advice, our research makes several important contributions to the literature. First, our study provides a more fine-grained analysis of the effects of robo-advisors. While most studies focusing on innovative self-service technologies have not considered relational implications (for an exception, see Giebelhausen et al. 2014), our research shows that the introduction of such technologies needs to be evaluated against the background of existing service relationships. In this respect, our research also follows recent calls to link the literature streams on self-service technologies and service relationships (e.g., Ostrom, Fotheringham & Bitner 2019; van Doorn et al. 2017).

Second, our research is also one of the first to address the question to what extent it is possible to automate advice. Our findings indicate that automating advice has clear boundaries in service contexts where a majority of customers maintains a communal relationship with a service provider. However, automating advice may affect customer relationships to a smaller extent in industries where customers predominantly follow exchange norms.

Third, our findings shed light on what firms can do to prevent that robo-advisors harm existing, communal relationships. In this regard, our results suggest that only hybrid robo-advice is able to offset the harmful impact of robo-advice. Contrary to our expectations, incorporating artificial support in the robo-advice process did not have a positive effect. In fact, artificial social support further reduced relationship quality. This finding provides a more nuanced view on the ability of service robots to accomplish inherently human tasks.

Conceptual Development

From Human Advice to Robo-Advice

Advice is a key offering of many professional service providers such as financial planners, tax consultants, or medical professionals (Seiders et al. 2015). Existing research has defined advice as an interpersonal process in which individuals consult with knowledgeable others before making complex decisions (Bonaccio & Dalal 2006; Schrah, Dalal & Sniezek 2006). Typically, these studies have operationalized advice as the provision of functional content such as recommendations or information regarding different alternatives. Several authors, however, have argued that advice often blends functional content with social support (Dalal & Bonaccio 2010; Goldsmith & Fitch 1997; MacGeorge et al. 2004). Specifically, observational studies show that advisors naturally combine functional content with various forms of social support such as acknowledging the importance and difficulty of a decision, expressing solidarity, or communicating encouragements and reassurances (e.g., Goldsmith & Fitch 1997; Morrow 2006). A nutrition consultant, for example, may not only recommend an optimal diet but may also empathize with her customer by acknowledging how difficult it is to change eating habits or by explaining that she has been in a similar situation in the past.

In view of these findings, one may argue that robo-advice differs fundamentally from human advice. Robo-advice requires customers to interact with a service robot that possesses a certain degree of AI instead of a human advisor (Huang & Rust 2018). For example, robo-advisors frequently use online questionnaires and chatbots to assess the initial situation of a customer, thereby rendering lengthy face-to-face conversations irrelevant. Similarly, the results of the advice process are not presented in personal meetings but become instantly available on-screen. If customers want to get additional advice, they do not need to contact their advisor but simply make changes to their settings. Moreover, human advice and robo-advice provide different forms of advice. While human advice blends functional advice with social support (e.g., Goldsmith & Fitch 1997; Morrow 2006), most robo-advisors only provide functional advice such as information on different options or recommendations. As a result, customers may have a less holistic advice experience than customers who receive advice from a human advisor.

While human advice and robo-advice may, thus, differ in fundamental respects, many service firms have introduced different variants of robo-advisors that are aimed to address these differences. First, while stand-alone robo-advisors fully substitute human advice by robo-advice (i.e., customers only interact with a machine), hybrid robo-advisors incorporate a human advice layer on top of the automated advice (Davenport, Libert & Beck 2018; Rai, Constantinides & Sarker 2019). An example would be an investment advisor who leads a customer through the robo-advice process or a health service provider that allows customers to discuss a diagnosis generated by robo-advice with a real doctor. Second, to make robo-advice more similar to human advice, firms have started to include artificial social support in the robo-advice process. For example, Replika, an app that lets users create an artificial friend, supplies people who feel anxious with socially supportive communication through a chatbot (Olson 2018). Hence, in this research, we distinguish between robo-advisors that operate on a stand-alone or a hybrid basis and stand-alone robo-advisors with and without artificial social support.

Different Types of Service Relationships

One of the core concepts of service research has been the concept of relationship marketing. As such, many scholars have emphasized that companies should strive to build, sustain, and enhance relationships with their customers, arguing that strong relationships lead to positive downstream effects such as increased loyalty and referral behavior (e.g., Hennig-Thurau, Gwinner & Gremler 2002; Mende, Bolton & Bitner 2013; Palmatier et al. 2006; Verhoef 2003). In this respect, relationship quality (i.e., customers' overall assessment of the strength of a relationship) is regarded as a key outcome of relationship marketing (e.g., Crosby, Evans & Cowles 1990; Hennig-Thurau, Gwinner & Gremler 2002; Palmatier et al. 2006). Relationship quality is typically conceptualized as a multidimensional construct reflecting different but interrelated facets of service relationships – namely, satisfaction with the relationship, trust in the service provider, and commitment to the relationship (De Wulf, Odekerken-Schroeder & Iacobucci 2001; Hennig-Thurau, Gwinner & Gremler 2002). Whereas satisfaction refers to customers' general assessment of the performance of a service firm, trust reflects their confidence in a service firm's reliability and integrity (Crosby, Evans & Cowles 1990; Doney & Cannon 1997). Commitment, on the other hand, is regarded as customers' attachment to a service provider and their desire to maintain the service relationship (De Wulf, Odekerken-Schroeder & Iacobucci 2001; Mende, Bolton & Bitner 2013). Against this background, we focus on relationship quality as the key outcome variable in our studies.

However, it is important to understand that customers may develop different *kinds* of relationships with their service providers. In this context, a prominent distinction in service and marketing research is the distinction between exchange and communal relationships (e.g., Aggarwal 2004, 2009; Bolton & Mattila 2015; Scott, Mende & Bolton 2013; van Doorn et al. 2017; Wan, Hui & Wyer 2011). According to social relationship theory (Clark & Mills 1979, 1993), exchange and communal relationships are governed by different norms that shape people's expectations of their relationship partners. In exchange relationships, partners follow a quid pro quo principle (Clark & Mills 1979) . When a relationship partner gives a benefit to the other partner, she/he is expected to receive a comparable benefit in return. In contrast, in communal relationships, partners are expected to genuinely care about each other's welfare, to mutually support each other without prompt reciprocation, and to not seek maximization of their own interests (Clark & Mills 1979).

While service relationships (like all business relationships) are typically characterized by exchange norms, these relationships are often complemented by communal norms (Aggarwal 2009; Goodwin 1996). For instance, in a relationship between a bank and a customer, exchange norms are salient because both partners are involved in commercial transactions. At the same time, however, many customers may perceive a certain level of communal norms as they have developed a friendly relationship with their bank. Importantly, research suggests that the extent to which customers perceive communal norms may vary considerably between customers (e.g., Clark & Aragón 2013; Scott, Mende & Bolton 2013; Wan, Hui & Wyer 2011). For example, bank customers who have frequent personal interactions with service employees may perceive communal norms more strongly than customers who have less personal contact with service employees (Goodwin 1996). In other words, while both exchange and communal norms may be present within a single service relationship, one set of norms is typically dominant, thus determining the nature of the relationship.

In the following sections, we develop a conceptual model that postulates that the impact of different kinds of robo-advisors will be determined by the norms that are characteristic of the relationship between the customer and the service provider (see also Figure 1). Specifically, we postulate that the extent to which a) robo-advisors with or without complementary human advice and b) robo-advisors with or without artificial social support affect relationship quality will be moderated by the extent to which customers have a communal or an exchange relationship with the service provider. We will first elaborate on how relationship type affects the impact of stand-alone vs. hybrid robo-advice, followed by a discussion of the interplay between artificial social support and relationship type.

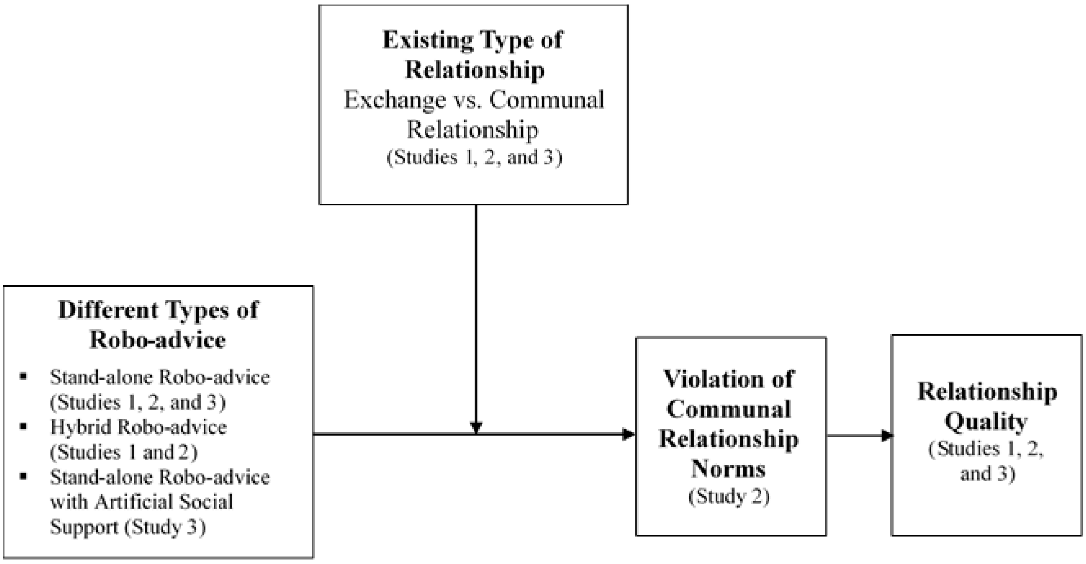

Figure 1. Conceptual model

The Impact of Stand-alone vs. Hybrid Robo-advice

As discussed above, practice and research differentiate between stand-alone and hybrid robo-advice. Arguably, the effect of these different kinds of robo-advice on relationship quality will depend on the type of relationship between a customer and a service provider. When customers have a communal relationship with their service provider, the introduction of stand-alone robo-advice (compared to hybrid robo-advice) may negatively affect relationship quality. In communal relationships, individuals expect their relationship partner to care about their welfare but not to seek maximization of own interests (Clark & Mills 1979). Building on this notion, customers may infer that a service provider that introduces a stand-alone robo-advisor merely wants to maximize the efficiency of the advice process and does not care about the norms that are characteristic of communal relationships. Moreover, as customers may have received social support from their human advisors in the past, they may believe that the firm does not want to provide this kind of support any longer. As social support conveys the impression that a relationship partner cares about the well-being of the other partner (Crocker & Canevello 2008), stand-alone robo-advice may be regarded as a violation of communal norms and should therefore lead to a lower level of relationship quality.

In contrast, when a hybrid robo-advisor is introduced, customers may not feel that communal norms are violated to the same extent. In this case, they may believe that the company still cares about the relationship with them and, thus, refrains from fully maximizing the efficiency of the advice process. In support of this idea, research suggests that individuals may infer the motives of a relationship partner based on the partner's willingness to forego an activity for the good of the relationship (i.e., the willingness to sacrifice potential benefits) (Wieselquist et al. 1999). In addition, hybrid advice may signal to customers that the company wants to continue providing social support by incorporating human advice in the robo-advice process. Hence, communal norms may be strengthened rather than violated (Crocker & Canevello 2008). This, in turn, may lead to a higher level of relationship quality. Therefore,

> H1a: In a communal relationship, customers will report a lower level of relationship quality when their service provider introduces a stand-alone robo-advisor (vs. a hybrid robo-advisor).

In contrast, when customers have an exchange relationship with a service provider, relationship quality may not differ as strongly across different types of robo-advice. In these relationships, people expect each other to follow a transactional logic but not to primarily care for each other's well-being (Clark & Mills 1979). Hence, when communal norms are not salient in the first place, the introduction of stand-alone robo-advice may not represent a violation of such norms. In fact, one may argue that stand-alone robo-advice is rather congruent with exchange norms as customers may expect the service firm to follow its own interests and may focus more strongly on the benefits that are provided by robo-advisors (Aggarwal 2009; Scott, Mende & Bolton 2013). As a result, they should care less about not having access to social support any longer and should respond similarly to both kinds of robo-advice. Put differently, customers who have been offered stand-alone robo-advice should exhibit a similar level of relationship quality as customers that have been offered hybrid robo-advice. Thus,

> H1b: In an exchange relationship, customers will report similar levels of relationship quality across stand-alone and hybrid robo-advisors.

Next, the underlying process is investigated. As argued above, social relationships are characterized by specific norms and people typically expect their relationship partners to adhere to these norms (Cialdini & Trost 1998). In a related vein, research has shown that customers also expect service providers to adhere to relational norms and respond negatively when they feel that these norms have been violated (Aggarwal

2004, 2009; Scott, Mende & Bolton 2013; Wan, Hui & Wyer 2011; Wentzel, Tomczak & Henkel 2014). For instance, Scott, Mende & Bolton (2013) showed that consumers in communal relationships evaluated a seller who violated communal norms less favorably because they considered the seller as less “warm”, that is, as less caring and helpful. Based on these findings, we postulate that the interactive effect between type of robo-advice and type of relationship will be mediated by perceived norm violation. That is, customers in a communal relationship will feel that a stand-alone robo-advisor (relative to a hybrid robo-advisor) violates communal norms and this perception, in turn, will decrease relationship quality. In contrast, customers in an exchange relationship will not feel that robo-advisors – regardless of which particular type is introduced – violate salient relational norms. As a result, they should perceive similar levels of relationship quality across different types of robo-advice. Thus,

> H2: Norm violation will mediate the interactive effect between type of robo-advice and type of relationship.

The Impact of Stand-alone Robo-advice With and Without Artificial Social Support

Self-service technologies are increasingly able to mimic human social support by behaving as though they have feelings and by responding to customers’ emotional states (Huang & Rust 2018; van Doorn et al. 2017). For example, mental health apps such as Woebot or Replika, offer socially supportive conversations with chatbots that mimic human interaction. Against this background, one may argue that the provision of artificial social support through robo-advice may help to mitigate the potentially negative effect of stand-alone robo-advisors that have been described in the previous hypotheses.

As discussed previously, individuals in a communal relationship expect others to take care of them. Provision of social support such as expressing understanding or reassuring another person is a behavior that directly addresses this expectation (Crocker & Canevello 2008). Specifically, social support conveys the impression that a relationship partner is concerned about the well-being of the other partner and therefore resonates with communal norms (Horowitz et al. 2001). Hence, customers in a communal relationship are likely to respond negatively to stand-alone robo-advisors that lack any kind of social support as they will feel that the service provider does not really care about catering to their emotional needs.

Importantly, however, social support can not only be provided through face-to-face conversations but also through online conversations (Yan & Tan 2014). In this respect, research has found that members of online advice forums regard written statements of social support provided by unacquainted internet users as genuine expressions of concern (Morrow 2006). As the form and content of such statements closely resemble the kind of social support provided by robo-advice chatbots, one may assume that customers in a communal relationship view social support provided by robo-advice as a legitimate expression of care and concern. Put differently, communally-oriented customers may feel that robo-advisors providing social support are more consistent with relational norms. Hence, they should experience a higher level of relationship quality when they interact with a robo-advisor that provides artificial social support compared to one that does not provide this kind of support.

> H3a: In a communal relationship, customers will report a higher level of relationship quality when their service provider introduces a stand-alone robo-advisor with artificial social support (vs. no artificial social support).

In contrast, customers in an exchange relationship may not respond differently to robo-advice with and without artificial social support. First, as mentioned above, customers under an exchange norm are likely to focus more strongly on the concrete benefits that are provided by robo-advice (Aggarwal 2004, 2009). Second, even if they perceive social support in a similar way as customers under a communal norm, this may not lead to a positive effect on relationship quality as the provision of social support does not resonate with exchange norms (Clark & Mills 1993; Crocker & Canevello 2008). That is, in an exchange relationship, a customer may expect a service provider to primarily follow a business interest and not to provide social support. Hence, customers may perceive the same level of relationship quality irrespective of whether artificial social support is provided or not. Therefore,

> H3b: In an exchange relationship, customers will report similar levels of relationship quality across stand-alone robo-advisors with or without artificial social support.

Pilot Study

One of the key notions of this research is that stand-alone robo-advice may harm relationship quality as many customers may perceive a mismatch between existing relationship norms and robo-advice. Before investigating this notion in an experimental setting, we wanted to gain initial support for this idea in a real-life setting. To this end, we conducted a pilot study with a small Swiss retail bank which had a net operating income of approximately USD 75 million per year. The bank had introduced a stand-alone investment robo-advice in 2014, and customers of the bank were given the choice to adopt the robo-advice or to continue receiving advice from a personal advisor. Importantly, however, customers were not able to use both robo-advice and human advice at the same time. We were allowed to send a short online questionnaire to 727 of the bank's customers and received a total of 124 usable responses (17% response rate; 79.84% male, average age: 57.09 years, average length of relationship: 25.74 years). Note that a high percentage of male customers is not unusual in an investment advice context.

In line with previous research (e.g., Hennig-Thurau, Gwinner & Gremler 2002), we conceptualized relationship quality as a higher-order construct that consists of satisfaction with a service firm's performance, trust in the firm, and commitment to the relationship. Specifically, to measure relationship quality, we relied on nine items from Mende, Bolton & Bitner (2013) that reflect these three dimensions and merged these items into a single construct (α = .94). All items of this study and the other studies used 7-point scales labelled *strongly disagree (1)* and *strongly agree (7)* if not stated otherwise. To control for extraneous influence, we included one-item measures of satisfaction with service quality, satisfaction with fees (endpoints: *very dissatisfied = 1, very satisfied = 7*), and perceived investment expertise of the bank (endpoints: *way below average = 1, way above average = 7*) (Crosby, Evans & Cowles 1990; Verhoef 2003). Moreover, we also controlled for several self-reported customer characteristics such as age, gender, length of relationship with the bank, and household income (ordinal scale with nine categories). However, as none of the characteristics of this latter set had a significant influence on relationship quality, they were excluded from the analysis.

Finally, customers' responses were matched with data from the bank's CRM database to determine whether customers used robo-advice or not. To operationalize robo-advice, we created a dummy-coded variable (0 = human advice, 1 = robo-advice). Of the 124 respondents, 90 used human advice and 34 used robo-advice. To test if robo-advice has a negative effect on relationship quality, we conducted several OLS-regression analyses. We estimated three different models that predicted relationship quality by type of advice only (base model), by the control variables only (controls models), and by all predictors conjointly (full model). Testing these models allowed us to analyze the robustness of the effect of robo-advice and to examine whether robo-advice explained incremental variance in relationship quality. Table 1 provides an overview of the different models. As expected, robo-advice had a negative impact in the base model (b = -.68, t = -3.51, p < .001) and in the full model (b = -.43, t = -3.09, p < .01). Moreover, the results indicate that robo-advice increases the amount of variance explained in relationship quality (controls model: R^2 = .58; full model: R^2 = .61).

In sum, these findings provide initial support for the notion that robo-advice may harm relationship quality. At the same time, these results need to be interpreted with caution as the respondents to our survey were not assigned randomly to human advice or robo-advice. Thus, the results may be affected by an oversampling of customers with a preference for one of these types of advice. To address this issue, the following studies rely on an experimental approach to obtain more conclusive evidence for the effect of robo-advice on customer relationships.

Table 1. Pilot Study: Regression Results for Relationship Quality

	Base model			**Controls model**			**Full model**		
	b	t	*p*	b	t	*p*	b	t	*p*
(Constant)	5.86	57.65	< .001	1.93	6.29	< .001	2.23	7.14	< .001
Robo-advice	-.68	-3.51	< .001				-.43	-3.09	< .01
Satisfaction with service quality				.35	4.90	< .001	.30	4.26	< .001
Satisfaction with fees				.11	2.32	.02	.15	3.14	< .01
Investment expertise				.26	4.18	< .001	.24	4.04	< .001
R^2	.09			.58			.61		

Study 1

Research Context

Study 1 was conducted with a sample of customers of a Swiss retail bank with an operating income of roughly USD 780 million per year. At the time of our study, the company did not offer robo-advice but planned to introduce robo-advice for pension planning. Our study was part of the development process of this new digital service and provided a first indication of how the bank's customers would react to the introduction of robo-advice.

Design, Procedure, and Participants

Study 1 was designed to test H1a and H1b. Participants were randomly assigned to a description of a stand-alone robo-advice or a hybrid robo-advice. In addition, we measured participants' type of relationship with the bank. To recruit participants for the study, the bank sent a physical mailing to 10,259 customers who had not used the bank's pension planning services so far. The mailing stated that the bank aimed to launch a new pension planning service and wanted to invite customers to take part in a pre-test of this service (importantly, the mailing did not make any reference to robo-advice). Participants were directed to a website where they were first asked to indicate their relationship with the bank and were then exposed to a detailed description of the new service and a first draft of the user interface. After looking at these materials at their own pace, participants responded to the dependent measures.

As an incentive, customers were offered the opportunity to take part in a raffle of ten shopping vouchers valued at roughly USD 100 each. In total, 448 customers participated in the study (53.6% male, average age: 39.1 years, average length of relationship: 21.1 years), resulting in a response rate of 4.4%. According to the bank's records, this represented an average response rate compared to other mailings.

Independent Variables

Relationship type was measured with a two-item scale from Scott, Mende & Bolton (2013) at the beginning of the study (see Appendix). This scale characterizes the nature of a relationship as exchange-oriented or communally-oriented, thereby reflecting the relative salience of different relationship norms. The individual scores were summed and averaged to form a relationship index ($\alpha = .75$).

The description of the pension planning service on the website stated that the bank planned to introduce a new online service based on financial algorithms that would advise customers on how to optimally save for retirement (i.e., a robo-advisor). Participants were told that the robo-advisor would rely on their personal information and financial objectives to project the monthly income they would need in retirement and to recommend financial products (e.g., savings plans, pension insurances) that would help them close the gap between their actual savings and the needed income. Importantly, in the stand-alone condition, participants were told that the service was designed as an alternative to human advice and that customers of the new service could *not* receive robo-advice *and* human advice at the same time. In contrast, in the hybrid condition, participants were told that the company planned to combine robo-advice and human advice and that customers could discuss the results of the robo-advice process with a human advisor. Moreover, the draft of the user interfaces slightly differed depending on the type of advice. That is, the user interface of the hybrid robo-advice included an additional setting that allowed customers to contact a human advisor.

Measures

Dependent measure. To measure relationship quality, we used six items from the scale used in the pilot study ($\alpha = .91$).

Manipulation check. As a check on the robo-advice manipulation, participants responded to one item ("[Bank] plans to offer the new robo-advice service in combination with human advice").

Control variables. As the bank did not offer robo-advice so far, robo-advice represented a new self-service technology for the participants of Study 1. According to research, acceptance of new technologies can be influenced by individual differences and by customers' expectations of the performance of these technologies (see Blut, Wang & Schoefer 2016 for an overview). Hence, to control for extraneous influence, we included several measures that have been found to influence the acceptance of new technologies (e.g., Venkatesh, Thong & Xu 2012). These measures included one-item measures of optimism ("New technologies contribute to better quality of life" (Parasuraman & Colby 2015)), need for interaction ("I like interacting with the person who provides the service" (Dabholkar 1996)), and performance expectancy of robo-advice ("Using [name of robo-advice service] helps me to plan retirement more successfully" (adapted from Venkatesh, Thong & Xu 2012)). Moreover, we measured perceived service quality with one item ("[Firm] has assisted me well to achieve my financial goals" (Bell, Auh & Smalley 2005)) and controlled for several self-reported customer characteristics (age, gender, relationship length, household income). Finally, we also assessed whether participants had a personal client advisor. Arguably, customers with a permanently assigned advisor may evaluate robo-advice differently than customers without one.

Analyses and Results

Manipulation check. Participants in the hybrid robo-advice condition believed more strongly that the bank wanted to combine robo-advice and human advice ($M_{\text{stand-alone}}$ = 3.43; M_{hybrid} = 5.68, $F(1, 426) = 44.54$, $p < .001$).

Control variables. Optimism, performance expectancy, and satisfaction with service quality emerged as significant covariates and were thus included in the analysis. All other variables did not have a significant impact and were thus excluded from the analysis.

Hypotheses testing. To test our hypotheses, we conducted an OLS regression analysis. In this regression, we mean-centered the relationship score and included it as a continuous predictor variable. Moreover, we included type of robo-advice and the interaction between type of robo-advice and type of relationship in the model and regressed relationship quality on these variables (see Table 2). This analysis revealed a significant interaction effect between type of robo-advice and type of relationship on relationship quality (b = -.16, t = -2.17, *p* = .03).

Next, we conducted simple slopes and spotlight analyses to examine the impact of the type of robo-advice at different levels of the relationship measure. When the relationship was of a communal nature (i.e., one standard deviation below the mean), the slope of type of robo-advice was positive and significant (b = .25, t = 2.19, p = .03). That is, participants who were exposed to a stand-alone robo-advice reported lower relationship quality than participants who were exposed to a hybrid robo-advice (Mstand-alone = 5.04; Mhybrid = 5.29). In contrast, when the relationship was exchange-oriented (i.e., one standard deviation above the mean), there was no significant effect of type of robo-advice (b = -.10, t = -.87, p = .38) and participants reported about the same level of relationship quality regardless of what type of robo-advisor was introduced (Mstand-alone = 4.91; Mhybrid = 4.81). These results provide support for H1a and H1b.

Table 2. Study 1: Regression Results for Relationship Quality

	Initial Regression			**Communal Relationship (- 1 SD)**			**Exchange Relationship (+ 1 SD)**		
	b	t	*p*	b	t	*p*	b	t	*p*
(Constant)	1.57	6.23	< .001	1.46	5.13	< .001	1.68	5.99	< .001
Type of robo-advice (stand-alone, hybrid advice)	.08	.93	.35	0.25	2.19	.03	-0.10	-.87	.38
Type of relationship	.10	.89	.38	.10	.89	.38	.10	.89	.38
Type of robo-advice × type of relationship	-.16	-2.17	.03	-.16	-2.17	.03	-.16	-2.17	.03
Optimism	.08	2.55	.01	.08	2.55	.01	.08	2.55	.01
Performance expectancy	.19	6.40	< .001	.19	6.40	< .001	.19	6.40	< .001
Satisfaction with service quality	.41	13.26	< .001	.41	13.26	< .001	.41	13.26	< .001
R^2	.43			.43			.43		

Discussion

Study 1 provides support for our conceptual framework and shows that the effect of different types of robo-advice is moderated by relationship type. That is, whereas the introduction of stand-alone robo-advice (relative to hybrid robo-advice) negatively affected relationship quality when customers had a communal relationship with the bank, relationship quality was not affected by different types of robo-advice when customers had an exchange relationship with the bank. One limitation of Study 1, however, is that we assessed many of our variables with relatively few items and did not include any measures designed to examine the underlying process. This limitation is due to the restrictions that were imposed by the bank regarding the overall length of the survey. To address these issues, we conducted an additional study that aimed to replicate and extend the results of Study 1.

Study 2

Design, Procedure, and Participants

The purpose of Study 2 was to replicate the findings of Study 1 and to test H2. Similar to Study 1, participants were randomly assigned to different robo-advice conditions (i.e., stand-alone advice vs. hybrid advice). Moreover, we also included a control condition in which participants did not receive a description of a robo-advisor. As in Study 1, we measured participants' relationship with the service provider that was the focus of this study (i.e., a regional bank in Germany). The sample consisted of 205 customers of this bank (50.2% male, average age: 34.2 years, average length of relationship: 16.2 years) that were recruited by students of a marketing class taught and supervised by one of the researchers. In line with previous research (e.g., Groth, Hennig-Thurau & Walsh 2009), we implemented several precautions to ensure the quality of the data. First, an initial pre-screening ensured that only customers of the bank were able to access the study. Second, we informed students that we would conduct random quality checks to verify honest and conscientious collection of data and that any misconduct would negatively impact their final grade.

The procedure of Study 2 was identical to Study 1. That is, participants were asked to visit a website where they were first asked to characterize their relationship with the bank and were then exposed to a description of a new online service for pension planning and a first draft of the user interface for this service. After reading through the materials, participants responded to the dependent measures and were debriefed.

Independent variables

To measure participants' relationship with the bank, we adapted the twelve-item measure of relationship norms from Clark and colleagues (Clark & Aragón 2013). As suggested by previous research (Aggarwal 2004; Scott, Mende & Bolton 2013), we formed a relationship index (α = .73) by averaging the communal and the reverse-coded exchange items. Hence, a higher value is indicative of a communal relationship, whereas a lower value reflects an exchange relationship. As indicated above, the manipulation of robo-advice (i.e., the descriptions of the new service and the draft of the interface) was identical to Study 1. Moreover, we also included a control condition where participants were not exposed to the new pension planning services and directly responded to the dependent measures (i.e., their relationship quality). This condition served as an additional benchmark in the analyses.

Measures

Dependent measure. Relationship quality was measured with the same items as in the pilot study (α = .95).

Process measure. To measure norm violation, we used the three-item norm violation scale from Aggarwal (2004; α = .95).

Manipulation check. As a check on the robo-advice manipulation, we used the same item as in Study 1.

Control variables. We included the same variables as in Study 1.

Analyses and Results

Manipulation check. Participants in the hybrid robo-advice condition believed more strongly that the bank wanted to combine robo-advice and human advice ($M_{\text{stand-alone}}$ = 3.58; M_{hybrid} = 6.17, $F(1, 68) = 36.61$, $p < .001$).

Control variables. Similar to Study 1, performance expectancy emerged as a significant covariate. In addition, need for interaction, household income, gender, and personal client advisor emerged as significant covariates and were included in the analyses. All other control variables did not have a significant impact and were thus excluded from the analysis.

Hypotheses testing. Similar to Study 1, we mean-centered the relationship variable and conducted an OLS regression (see Table 3, model 1). This analysis revealed a significant interaction effect between type of robo-advice and type of relationship (b = .70, t = 3.10, p < .01). To follow up on this effect, we conducted simple slopes and spotlight analyses. When participants had a communal relationship with their bank (i.e., one standard deviation above the mean), the slope of type of robo-advice was positive and significant (b = .59, t = 2.05, p = .04). Hence, participants who had been exposed to hybrid robo-advice reported a higher level of relationship quality compared to participants who had been exposed to the stand-alone robo-advice ($M_{\text{stand-alone}}$ = 4.14, M_{hybrid} = 4.73). These findings support H1a.

However, when customers had an exchange relationship (i.e., one standard deviation below the mean), the slope was negative and significant (b = -.68, t = -2.48, p = .01). That is, customers perceived a higher level of relationship quality when they had been exposed to the stand-alone compared to the hybrid robo-advice ($M_{\text{stand-alone}}$ = 4.55, M_{hybrid} = 3.86). Interestingly, these findings differ somewhat from the effects postulated in H1b. While we expected to find similar levels of relationship quality across the two types of robo-advice, the results suggest that exchange-oriented customers respond more positively to stand-alone robo-advisors than to robo-advisors that are combined with a human feedback element.

Table 3. Study 2: Regression Results for Relationship Quality

	Initial Regression			**Communal Relationship (+ 1 SD)**			**Exchange Relationship (- 1 SD)**		
	b	t	*p*	b	t	*p*	b	t	*p*
Model 1									
(Constant)	4.64	8.28	< .001	4.44	7.72	< .001	4.85	8.40	< .001
Type of robo-advice (stand-alone, hybrid advice)	-.05	-.25	.80	.59	2.05	.04	-.68	-2.48	.01
Type of relationship	-.22	-1.52	.13	-.22	-1.52	.13	-.22	-1.52	.13
Type of robo-advice × type of relationship	.70	3.10	< .01	.70	3.10	< .01	.70	3.10	< .01
Need for interaction	.13	2.43	.02	.13	2.43	.02	.13	2.43	.02
Performance expectancy	.31	5.40	< .001	.31	5.40	< .001	.31	5.40	< .001
Personal client advisor	-.89	-4.40	< .001	-.89	-4.40	< .001	-.89	-4.40	< .001
Gender	-.37	-1.85	.07	-.37	-1.85	.07	-.37	-1.85	.07
Household income	-.07	-1.90	.06	-.07	-1.90	.06	-.07	-1.90	.06
R^2	.43			.43			.43		
Model 2									
(Constant)	5.36	11.57	< .001	5.71	12.26	< .001	5.71	12.26	< .001
Dummy 1 (control, stand-alone advice)	-.26	-1.29	.20	-1.06	-3.73	< .001	.53	1.82	.07
Dummy 2 (control, hybrid advice)	-.06	-.30	.77	.13	.46	.65	-.25	-.80	.43
Type of relationship	.41	2.13	.03	.41	2.13	.03	.41	2.13	.03
Dummy 1 × type of relationship	-.91	-3.87	< .001	-.91	-3.87	< .001	-.91	-3.87	< .001
Dummy 2 × type of relationship	.22	.86	.39	.22	.86	.39	.22	.86	.39
Need for interaction	.18	3.91	< .001	.18	3.91	< .001	.18	3.91	< .001
Personal client advisor	-.62	-3.48	< .001	-.62	-3.48	< .001	-.62	-3.48	< .001
Gender	-.29	-1.68	.10	-.29	-1.68	.10	-.29	-1.68	.10
Household income	-.10	-2.94	< .01	-.10	-2.94	< .01	-.10	-2.94	< .01
R^2	.30			.30			.30		

Process analysis. Our framework proposes a case of moderated mediation, in which type of relationship moderates the effect of type of robo-advice on norm violation which, in turn, affects relationship quality (Hayes 2018; model 7). To examine this proposition, we ran a mediation analysis (5,000 bootstrap samples) with the above-mentioned variables and the control variables as covariates. In the mediator model, the advice × relationship interaction had a significant impact on norm violation (-.86, 95% CI = [-1.43; -.29]). In the dependent variable model, norm violation emerged as a significant predictor of relationship quality (-.21, 95% CI = [-.34; -.08]) but the direct effect of type of robo-advice was not significant (-.17, 95% CI = [-.56; .21]). The confidence interval for the index of moderated mediation did not include zero (.18, 95% CI = [.02; .39]), indicating a mediation effect of norm violation.

To follow up on this effect, we compared the impact of robo-advice through norm violation on relationship quality when a customer had a communal (i.e., one standard deviation above the mean) and an exchange relationship (i.e., one standard deviation below the mean). This analysis revealed a significant indirect effect of type of advice on relationship quality through norm violation for communal customers (.30, 95% CI = [.06; .62]) but not for exchange customers (-.02, 95% CI = [-.19; .14]). These findings support H2.

Additional analyses. To gain additional insights into the effects caused by different types of robo-advice, we compared the stand-alone and the hybrid robo-advice conditions to the control group (see Table 3, model 2). To this end, we created two additional dummy variables (i.e., one dummy comparing the control condition to stand-alone robo-advice and one dummy comparing the control condition to hybrid robo-advice) as well as two interaction terms between type of relationship and these variables. Note that we did not include performance expectancy in this model because this variable did not apply to the control condition. The initial regression revealed a significant interaction effect between the dummy variable comparing the control condition to stand-alone robo-advice and type of relationship (b = -.91, t = -3.87, p < .001). The interaction between the dummy variable comparing the control condition to hybrid robo-advice and type of relationship was not significant (b = .22, t = .86, p = .39).

When participants had a communal relationship with their bank (i.e., one standard deviation above the mean), there was a significant, negative effect of the dummy variable comparing the control condition to stand-alone robo-advice (b = -1.06, t = -3.73, p < .001) but no significant effect of the dummy variable comparing the control condition to hybrid robo-advice (b = .13, t = .46, p = .65; M_{control} = 4.83, $M_{\text{stand-alone}}$ = 3.77, $M_{\text{hybrid robo-advice}}$ = 4.96). On the other hand, when participants had an exchange relationship with the bank (i.e., one standard deviation below the mean), a different pattern emerged. In these cases, the dummy comparing the control condition to stand-alone robo-advice had a positive and marginally significant effect (b = .53, t = 1.82, p = .07), whereas the dummy comparing the control condition to hybrid robo-advice had no effect (b = -.25, t = -.80, p = .43; $M_{control}$ = 4.12, $M_{stand\text{-}alone}$ = 4.66, M_{hybrid} = 3.87). These results are also summarized in Figure 2 and discussed in greater detail in the following section.

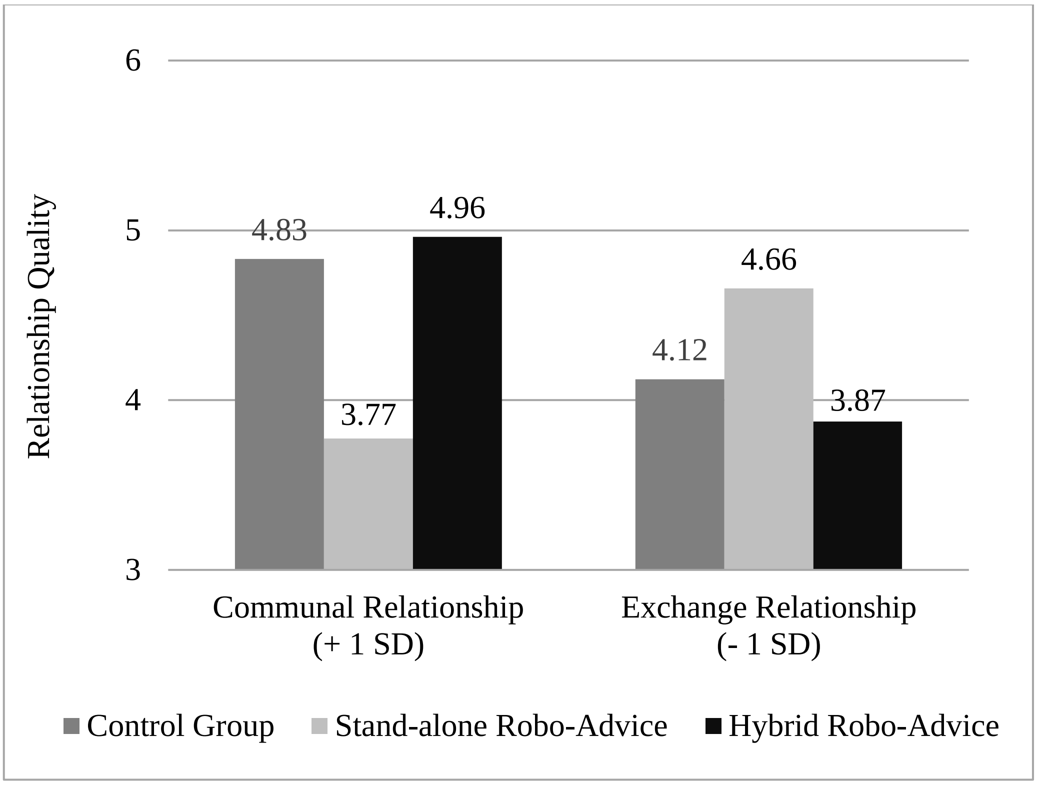

Figure 2. Effect robo-advice type and control group on relationship quality

Discussion

Replicating the results of Study 1, Study 2 finds that the introduction of stand-alone robo-advice (relative to a hybrid one) negatively affected relationship quality for communally-oriented customers and also showed that this effect was driven by a perceived violation of relationship norms. Moreover, a comparison of the two robo-advice types to the control condition revealed additional insights on how robo-advice affects relationship quality. That is, these analyses showed that stand-alone robo-advice decreased relationship quality compared to the control condition, while there was no difference between the control condition and hybrid robo-advice. Put differently, combining robo-advice with a human component may help to maintain the relationships that customers experience before these technologies are introduced.

A somewhat different pattern of effects emerged for exchange-oriented customers. That is, while we expected to find no differences between the two types of robo-advice, the results of Study 2 showed that relationship quality was actually *higher* when a stand-alone robo-advice (compared to a hybrid one) was introduced. Arguably, a stand-alone robo-advisor may be more congruent with the tit for tat mentality that is characteristic of exchange relationships compared to a hybrid robo-advisor that adds a human element to the advice process that may not be strictly necessary. Again, the control condition provides some tentative support for this reasoning by showing that participants experienced a *higher* relationship quality in the stand-alone condition than in the control condition.

Study 3

Design, Procedure, and Participants

The aim of Study 3 was to test H3a and H3b. In addition, to increase the generalizability of our results, we made two changes to our research design. First, as previous research suggests that relationships norms can be evoked in a laboratory setting (Aggarwal 2009; Clark & Mills 1993), we manipulated rather than measured different relationship types in Study 3. Second, we focused on a different service context, namely, medical diagnosis and advice.

Study 3 used a 2 (type of relationship: exchange, communal) $\times$ 2 (type of robo-advice: with, without artificial social support) between-subjects design. A total of 112 participants (67% male, average age: 23.0 years) recruited through the subject pool of a large German university took part in the study in return for a financial incentive. Participants were invited to a behavioral lab where they were seated individually at a computer workplace. At the beginning of the study, participants read a scenario between a patient and a medical center for dermatology that was designed to elicit different types of relationships and that was adapted from Aggarwal (2004). After reading the relationship scenario, participants responded to the first manipulation check. Next, they were informed that the medical center had recently introduced a robo-advice service called “OnlineDerma” that aimed to examine birthmarks with the help of diagnostic imaging technology. Participants were asked to imagine that they had uploaded a picture of one of their own birthmarks and to go through an examination of this birthmark with the help of the robo-advisor (more details follow below). After completing the examination, participants responded to the dependent measures and were debriefed about the true purpose of the study.

Independent Variables

To manipulate relationship type, participants were asked to read a description of a relationship between a patient and a dermatology center and to project themselves into the role of the patient. In half of the conditions, the description featured communal norms (e.g., “In almost every appointment, you had a pleasant and warmhearted conversation with the attending physician which was not only about medical issues. The Luisen Dermatology Center seems to be taking a personal interest in you”). In the other half, the description featured exchange norms (e.g., “During your last visits, the Luisen Dermatology Center offered other services to you such as a special skin cancer screening which appeared to be of great value and was offered to you at a low price”). Similar manipulations have been used successfully in previous studies on service relationships (Aggarwal 2004, 2009; Wan, Hui & Wyer 2011).

To manipulate social support, participants were told that the medical center had recently launched an online service that could generate a recommendation on whether a birthmark needed to be removed without any intervention of a human dermatologist. Participants were asked to refer to one of their own birthmarks and to imagine that they had uploaded a picture of their birthmark. Next, they were asked to visit the website of this new service and to go through an online examination of the birthmark. To this end, we created a website that included a chatbot that participants could interact with. This chatbot asked participants several questions about this birthmark, for example, if the birthmark itched or had an asymmetric shape (Figure 3 shows examples of the dialogue with the chatbot). Importantly, in the no-social-support condition, the questions and statements of the chatbot were strictly factual and did not include socially supportive elements. In contrast, in the social-support conditions, the chatbot made several socially supportive statements (e.g., “I understand that one worries when examining a birthmark”, “I want to be there for you and support you as best as possible with my diagnosis”). Apart from these statements, all participants received the same information. After several rounds of questions and answers, the chatbot stopped and announced that it had sufficient information and that it would send an email report of the results and its recommendation to participants (note that participants were thoroughly debriefed and informed that the robo-advice did not actually perform an analysis of their birthmark).

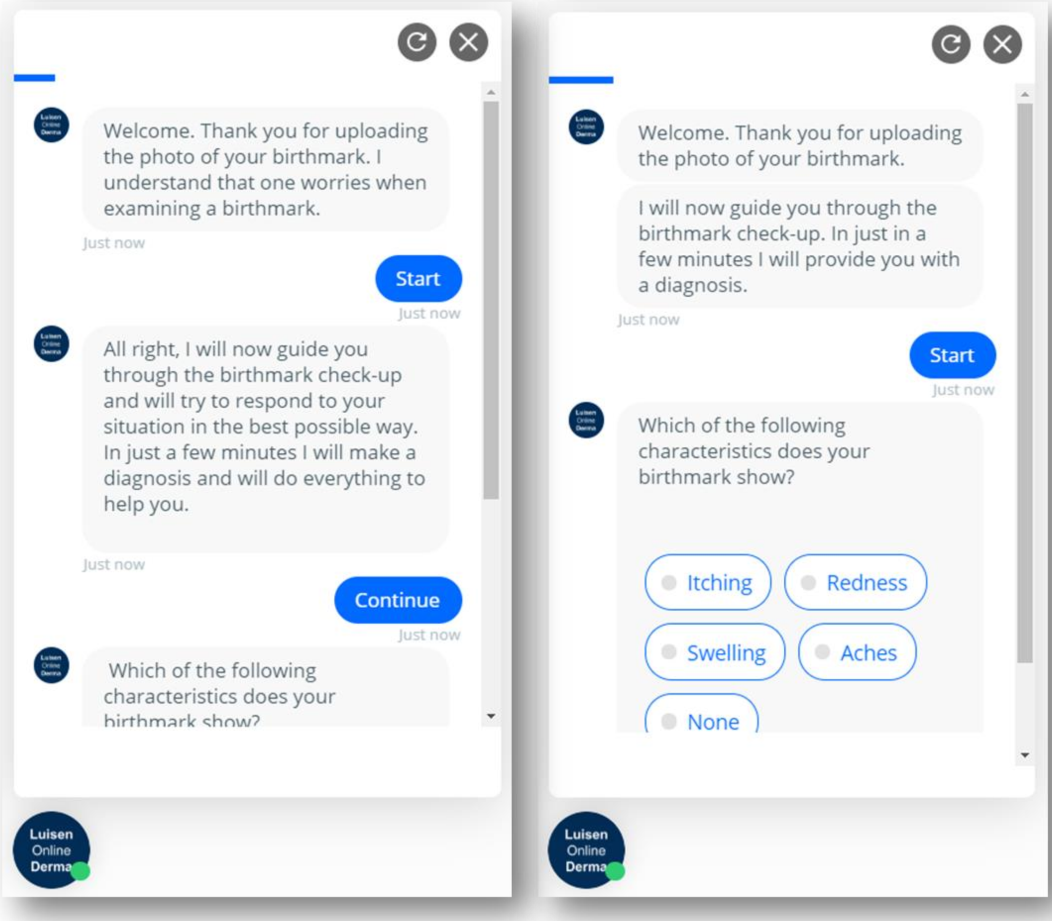

Figure 3. Screenshots of chatbot dialogues with and without social support

Measures

Dependent measures. We measured relationship quality with the same items as in the pilot study and in Study 2 (α = .91).

Manipulation checks. As a check on the relationship manipulation, we used the two-item type of relationship scale from Study 1 (α = .84). Moreover, participants indicated on three items the degree to which they believed that the robo-advisor had provided social support (“OnlineDermatologist empathized with me”, “OnlineDermatologist cared about me”, “Using OnlineDermatologist I had the feeling that OnlineDermatologist was there for me”, α = .85).

Control variables. We included the same variables as in Study 1 and 2. The measure for performance expectancy was adapted to the new context ("Using OnlineDermatologist helps me to better care for my health").

Analyses and Results

Manipulation checks. Participants in the communal conditions believed more strongly that they had a communal relationship with the medical center than participants in the exchange conditions ($M_{\text{communal}} = 2.69$, $M_{\text{exchange}} = 3.87$, $F(1, 108) = 19.09$, $p < .001$). Moreover, participants perceived a stronger degree of social support in the conditions with artificial social support than in the conditions without artificial social support ($M_{\text{with social support}} = 4.58$, $M_{\text{without social support}} = 3.32$, $F(1, 108) = 17.96$, $p < .001$).

Control variables. Performance expectancy ($F(1, 106) = 18.83$, $p < .001$) and need for interaction ($F(1, 106) = 6.98$, $p < .01$) emerged as significant covariates in the analyses. All other variables did not emerge as significant covariates and were thus excluded from the analysis.

Hypotheses testing. A 2 × 2 ANCOVA revealed insignificant effects for type of robo-advice ($F(1, 106) = 1.35$, $p = .25$) and type of relationship ($F(1, 106) = 2.31$, $p = .13$) on relationship quality. More importantly, the interaction between these variables was significant ($F(1, 106) = 3.55$, $p = .06$). However, contrary to expectations, participants in the communal conditions perceived a lower relationship quality when they interacted with a robo-advisor with artificial social support than when they interacted with a robo-advisor without support ($\text{M}_{\text{with social support}} = 5.79$, $\text{M}_{\text{without social support}} = 6.24$, $F(1, 106) = 4.52$, $p = .04$). In contrast, participants in the exchange conditions reported a similar level of relationship quality regardless of which type of robo-advice was introduced ($\text{M}_{\text{with social support}} = 5.84$, $\text{M}_{\text{without social support}} = 5.73$, $F(1, 106) = .26$, $p = .61$). In sum, these findings provide support for H3b but not H3a.

Discussion

Study 3 extends the findings of the previous studies and shows that the impact of robo-advisors featuring socially supportive elements is moderated by the type of relationship that customers have with a service provider. Specifically, the results suggest that robo-advisors with artificial social support may reinforce the negative effect of stand-alone robo-advice when customers have a communal relationship. However, when customers have an exchange relationship, the presence or absence of social support may make little difference in terms of relationship quality. These findings contradict our hypothesis that adding artificial social support (thereby adding a “human” element) to robo-advisors will help improve the responses of communally-oriented customers to these technologies. A more detailed discussion of this surprising finding is provided in the next section.

General Discussion

Many scholars have argued that services may be at the dawn of a new era in which high-touch services that have typically been performed by human service providers may be replaced by self-service technologies relying on AI (Marinova et al. 2016; van Doorn et al. 2017). In this context, high hopes are placed on robo-advice tools that may assist customers in digital service frontlines. At the same time, human employees in professional service jobs are predicted a bleak future (Huang & Rust 2018). However, there is a lack of studies that examine how robo-advice may affect service relationships and how human advice and robo-advice may interact in the service frontline. Against this background, this research sought to examine the impact of robo-advice on service relationships.

The data supported our basic notion that stand-alone robo-advice, that is, robo-advice without any integration of human advice, may have a negative effect on service relationships. Specifically, Studies 1 and 2 showed that stand-alone robo-advice reduces relationship quality for customers that have a communal relationship with their service provider compared to hybrid robo-advice that combines robo-advice and human advice or a control condition without any type of robo-advice. On the other hand, no such differences or even a reverse pattern of results were found for customers that had an exchange relationship with their service provider. Study 2 also demonstrated that norm violation mediated the interactive effect type of robo-advice and type of relationship on relationship quality. Finally, Study 3 examined if responses to robo-advisors may be improved by adding artificial social support. However, our results indicate that this strategy may backfire for customers with a communal relationship. Contrary to our expectations, robo-advisors that were enhanced with artificial social support led to an even stronger reduction of relationship quality compared to robo-advisors without social support.

Research Implications

These findings make several contributions to service research. First, our research is one of the first to investigate the impact of robo-advice in different relationship contexts. As such, most research on new technologies in the service frontline has not considered the relational aspects that may be affected by the introduction of such technologies (for an exception, see Giebelhausen et al. 2014). Our findings, however, suggest that it is of high importance to consider the relational implications of self-service technologies. That is, although self-service technologies like robo-advice may lead to a more efficient service process (e.g., Bitner, Brown, & Meuter 2000), they may also have a negative impact on relationship quality. Specifically, our findings suggest that stand-alone robo-advice may harm a communal relationship as this type of robo-advice does not fulfil customers' relationship expectations. Hence, our research identifies an important limitation of robo-advice and points to the necessity to consider relationship aspects when introducing self-service technologies such as robo-advice.

Second, by examining if and to what extent it is possible to automate advice, this research contributes to research on professional services (e.g., Dalal & Bonaccio 2010; Seiders et al. 2015). In this respect, our studies indicate that the automation of advice may have detrimental effects in industries where customers frequently have communal relationships with their service providers such as health care (van Doorn et al. 2017). Specifically, our results show that stand-alone robo-advice is incompatible with the norms of communal service relationships (e.g., care, mutual support) even when these norms are addressed through such means as artificial social support. In contrast, the introduction of robo-advice may have neutral or even favorable effects in industries where customers typically have an exchange relationship with their service providers (e.g., business consulting, tax advice). That is, in advice contexts that are more strongly based on exchange norms, stand-alone robo-advisors may not be considered at odds with extant relational norms. In sum, these findings add to research on professional services by providing a theoretical groundwork for understanding the impact of robo-advice.

Third, this research sheds light on what service firms can do to avoid relationship damages when introducing robo-advice to customers with communal relationships. In this respect, we tested two different options which, to the best of our knowledge, have not been examined so far – namely, hybrid robo-advice (i.e., placing a human advice layer on top of the robo-advice process) and stand-alone robo-advice with artificial social support. Importantly, our studies show that only hybrid robo-advice may be able to offset the potentially harmful impact of robo-advice in communal relationships. Artificial social support, in contrast, may reduce rather than increase relationship quality compared to stand-alone robo-advice. This finding is counterintuitive as previous research has linked the provision of social support to higher relationship satisfaction in communal relationships and has argued that social support can be effectively provided online (Crocker & Canevello 2008; Yan & Tan 2014).

To account for this finding, at least two potential explanations may be forwarded. First, artificial social support provided by a robo-advisor may not be seen as genuine care but as a display of fake emotions. That is, customers may not believe that machines have real feelings and may therefore mistrust the intentions of the service provider (van Doorn et al. 2017). Notably, research suggests that individuals regard social support provided out of self-interest as a violation of communal norms (Crocker & Canevello 2008). Second, robo-advice that provides artificial social support may elicit feelings of creepiness (Ostrom, Fotheringham & Bitner 2019). The so-called “uncanny valley” effect suggests that artificial service agents that appear relatively human but are perceived as non-human can evoke aversion (Mende et al. 2019; Mori, MacDorman & Kageki 2012). Hence, customers may consider robo-advisors that provide social support as creepy and may even feel frightened. In other words, while stand-alone robo-advisors may generally be incompatible with communal norms, adding a level of artificial social support may further undermine communal service relationships.

In sum, these findings are noteworthy as they provide a nuanced view on the ability of intelligent agents to accomplish inherently human service tasks such as providing social support (Huang & Rust 2018; Ostrom, Fotheringham & Bitner 2019). That is, our research suggests that although technology may be able to mimic human social behavior, many customers may perceive such behavior differently when it originates from an algorithm. These findings also offer an empirical justification for the impetus of many service companies to introduce hybrid robo-advice to their customers instead of stand-alone robo-advice.

Managerial Implications

The issues addressed in this research also have managerial implications. The most straightforward one is that service managers need to recognize that the implementation of robo-advice tools may be a double-edged sword. Whereas robo-advice may, on the one hand, increase service efficiency, on the other hand, it may also negatively affect existing service relationships. Hence, managers are well-advised to segment their customer base according to their dominant relationship type and offer each segment a type of robo-advice that matches their relationship needs. If customers have a communal relationship with a service firm, managers should abstain from fully substituting human advice by robo-advice as this may cause severe relationship damages. For example, many customers in private wealth management are used to having a personal, communal relationship with their bank. In such cases, firms should offer hybrid solutions that combine robo-advice and human advice. In this respect, firms could follow a task augmentation approach (Rai, Constantinides & Sarker 2019). For example, a human advisor could lead a customer through the robo-advice process and provide social support, while the robo-advisor analyzes the needs of the customer and generates different decision alternatives. In contrast, if customers have an exchange relationship with a service provider, the introduction of stand-alone robo-advice may not harm relationship quality. For example, bank customers who manage their finances themselves are likely to have an exchange relationship with their bank and may therefore not view robo-advice as a violation of relationship norms.

On a more general level, our findings suggest that two common strategic initiatives in services – relationship marketing and service automation – may not always be compatible. As such, many service firms are focused on establishing communal relationships with their customers as these relationships are expected to create greater loyalty (Goodwin 1996; Hennig-Thurau, Gwinner & Gremler 2002; Price & Arnould 1999). Our findings tentatively suggest that managers may undermine their efforts to build such relationships when offering a type of robo-advice that does not align with communal norms. Thus, it seems important that managers closely evaluate the strategic ramifications of robo-advisors before introducing such technologies. That is, if there is a strategic focus on communal relationships, managers may be well-advised to maintain a human element when infusing robo-advice in the service process.

Limitations and Future Research

Our studies also have limitations that call for future research. First, in our studies, participants were either told that their service provider would introduce robo-advice in the future and were asked to evaluate a prototype of this tool (i.e., Studies 1 and 2) or examined a robo-advisor in the context of a fictitious setting (i.e., Study 3). Thus, one limitation of our studies is that participants did not use these tools for actual decisions. While the results of the pilot study provide support for the notion that the implementation of robo-advisors may undermine service relationships in real life, future studies may want to examine if our findings regarding different types of robo-advice can also be validated in a field setting.

Second, we did not examine how variables related to the situational context may affect customer reactions to robo-advice. For instance, the level of emotional distress may vary greatly depending on the advice setting. A seriously ill patient receiving medical advice, for example, may experience greater emotional distress than a customer receiving investment advice from a bank. Arguably, such factors may influence the need for social support in the advice process, leading to a stronger preference for human advice or hybrid robo-advice. Investigating the interplay between robo-advice and different advice situations may therefore represent a fruitful area for future research.

Third, we focused on existing service relationships. However, it would also be interesting to investigate how robo-advice affects the formation of *new* relationships. Based on our findings, one may speculate that robo-advice will make it more difficult for firms to build communal relationships with their customers as robo-advice reduces interpersonal exchange (e.g., Goodwin 1996). Such research would be of great theoretical and practical interest as studies on personal and service relationships suggest that the perceived communality of a relationship is positively related to relationship satisfaction (e.g., Le et al. 2018; Price & Arnould 1999).

Finally, it may be of interest to investigate the impact of different robo-advice designs more closely. For example, van Doorn et al. (2017) suggested that anthropomorphizing a digital agent may make customers feel more strongly that they interact with another social entity. In light of the findings of Study 3, however, one may ask whether designing an anthropomorphic robo-advisor increases or decreases relationship quality in communal and exchange relationships. Similarly, future research may focus on the design of hybrid robo-advice. To date, we do not know how robo-advice and human advice should be combined to augment each other and to function as an integrated system.

While a number of issues remain to be explored, this research extends the literature in two important ways. First, it shows that service firms that are considering implementing robo-advice tools in their service processes need to consider the effects of these technologies on their existing customer relationships. Second, and more importantly, it also shows what service firms can do to avoid relationship damages when introducing robo-advice tools, especially when their customers share a communal relationship with the firm.

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Appendix Essay III

Appendix 1. Constructs and Measurement Items by Study

Construct	Wording of Measurement Items	Pilot Study	Study 1	Study 2	Study 3
Relationship quality (Mende, Bolton, and Bitner 2013)	• I am satisfied with [firm]. • I am content with [firm]. • I am happy with [firm].* • [Firm] is trustworthy. • [Firm] keeps promises.* • [Firm] is truly concerned about my welfare. • I enjoy being a customer of [firm]. • I have positive feelings about [firm].* • I feel attached to [firm].	X	X	X	X
	Coefficient α	.94	.91	.95	.91
Type of relationship (Scott, Mende, and Bolton 2013)	Please characterize the nature of your relationship with [firm]: • nurturing (1)/fair exchange (7) • caring personal (1)/efficient business (7)		X		X
	Coefficient α		.75		.84
Relationship norm (adapted from Clark and Aragón 2013)	• [Firm] and their employees treat me in a selfless manner and care about my needs. • When making a decision, I take the needs and feelings of [firm] and their employees into account. • [Firm] and their employees are especially sensitive to my feelings. • [Firm] and their employees are responsive to my needs and feelings. • If [firm] and their employees need my support, I would help them. • When I have a need that [firm] and their employees ignore, I'm hurt. Exchange norms • When I select the services of [firm], I generally expect something in return. • [Firm] and their employees should feel obligated to repay favors I have done to them. • I would feel exploited if [firm] and their employees failed to repay me for a favor. • I keep track of benefits I have given to [firm] and their employees. • When I select the services of [firm], [firm] and their employees ought to return the favor right away. • When I do business with [firm] and their employees, they pay me back adequately.			X	
	Coefficient α			.73	
Norm violation (Aggarwal 2004)	Imagining using the presented robo-advice tool in the future, I... • felt cornered • felt irritated • felt exploited			X	
	Coefficient α			.95	

*Item was not used in Study 1.