Digitalization of the individual –

Consequences, design, and behavior

Dissertation

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Abstract

In the past decades, digitalization has increasingly influenced our daily lives and habits in almost all areas and has even become indispensable for individuals, organizations, and society. The interactions between individuals and organizations have changed significantly as digitalization extends the boundaries of organizations to the point at which it affects individuals. Consequently, new research efforts and better understanding are essential to understand how the behavior of individuals is affected by the use of digital technologies, how customers' demands change, and how the purchasing process of organizations needs to be adapted.

Currently, the literature on digital transformation is mainly treating the organizational perspective. Nevertheless, organizations should not neglect the individual perspective as it is essential to understand customer needs and their consequences affected by digital technologies. Matt et al. (2019)[1] present a holistic research framework with three research perspectives for the digitalization of the individual. This framework encompasses the behavior of individuals, the design of information systems, and the consequences that digitalization entails. Additionally, this research framework suggests that a digitized individual can take on different roles, namely the individual itself, as a social being, citizen, customer, and employee. The dissertation uses this framework of Matt et al. (2019)[1] to structure and classify the covered contents and research objectives.

The aim of this dissertation is to contribute to a comprehensive overview for organizations to understand their customers' concerns regarding digital technologies, which design options they have to address these concerns, and how it influences their behavior to realize the potential of the technologies or reduce their harms. Therefore, this work applies pluralistic methodological approaches (qualitative methods, e.g., semi-structured interviews and qualitative content analysis, and quantitative methods, e.g., quantitative decision models and data collection from online questionnaires). With that, the dissertation provides novel insights for organizations to better implement digital technologies by regarding the consequences for individuals and the behavior of individuals.

First, to contribute to an understanding of the negative consequences digitalization can bring along for individuals, part A of this dissertation presents two research articles that focus on the concerns of individuals. The research papers P1 and P2 show in two different domains

[1] Matt, C., Trenz, M., Cheung, C. M. K., & Turel, O. (2019). The digitization of the individual: Conceptual foundations and opportunities for research. Electronic Markets, 29(3), 315–322.

what individuals are concerned about when using digital technologies and what prevents individuals from using them. P1 focuses on those concerns that arise with the use of automated decision-making. P2 takes a closer look at the concerns that patients and professionals have about the digital transformation in healthcare. Therefore, this dissertation presents knowledge about the fears and concerns of the individuals have and offers starting points to develop responsible and transparent digital technologies that address the concerns of the individuals.

Second, to contribute to design approaches for information systems that enable organizations to increase customer satisfaction with digital products and services, part B presents design approaches that organizations can use to address individuals' perceived consequences and change their behavior using digital technologies. Both research papers in part B present quantitative decision models as decision support for organizations. P3 develops a quantitative decision model that enables organizations to make informed decisions on whether or not to integrate certain customers in their business processes, all while accounting for the necessary customer support. P4 provides a formal decision model on customer relation recovery investments. Thus, this dissertation offers two design approaches that provide organizations with information on designing technologies to serve digitized individuals and foster them better to make well-founded decisions when introducing digital technologies.

Third, to contribute to the understanding of why and how individuals behave in certain ways and how this behavior can be influenced, Part C examines the behavior of individuals when using digital technologies. Research paper P5 develops a metric to better explore the privacy paradox - the irrational inconsistency between individuals' actual behavior and their theoretical concerns about disclosing their private information when using digital technologies. With that, this dissertation offers a basis, especially to researchers and individuals, to prevent unwanted behavior when using digital technologies.

To sum up, this dissertation contributes to scientific knowledge in research on the digitalization of the individual and thus addresses a subject of fundamental importance in this digital age. The models and approaches developed in this dissertation explore ways to improve conditions for the digitized individual at all three research perspectives – consequences, design, and behavior – with equal regard for the individual as itself and the individual as a customer.

Zusammenfassung

In den vergangenen Jahrzehnten hat die Digitalisierung zunehmend unseren Alltag und unsere Gewohnheiten in fast allen Bereichen des Lebens beeinflusst und ist damit für Individuen, Organisationen und die Gesellschaft unverzichtbar geworden. So hat sich die Beziehung zwischen Individuen und Organisationen erheblich verändert, da die Digitalisierung die Organisationsgrenzen aufweicht und ihre Kundinnen und Kunden mehr integriert. Folglich sind neue Forschungsanstrengungen und ein besseres Verständnis erforderlich, um nachvollziehen zu können, wie das Verhalten von Individuen durch den Einsatz digitaler Technologien beeinflusst wird, wie sich die Anforderungen von Kundinnen und Kunden ändern und wie der Kaufprozess von Organisationen angepasst werden muss.

Derzeit wird in der Literatur zum Themengebiet der digitalen Transformation hauptsächlich die organisationale Perspektive behandelt. Nichtsdestotrotz sollten Organisationen die individuelle Perspektive nicht vernachlässigen. Sie ist grundlegend, um die Kundenbedürfnisse, die durch digitale Technologien beeinflusst werden, und deren Folgen zu verstehen. Matt et al. (2019)[1] stellen einen ganzheitlichen Forschungsrahmen mit drei Forschungsperspektiven für die Digitalisierung des Individuums vor. Dieser umfasst das Verhalten der Individuen, die Gestaltung von Informationssystemen und die Konsequenzen, die die Digitalisierung für Individuen mit sich bringen kann. Zusätzlich zeigt dieser, dass ein digitalisiertes Individuum verschiedene Rollen einnehmen kann, wie die Rolle als Individuum selbst, als soziales Wesen, als Bürgerin oder Bürger, als Kundin oder Kunde und als Mitarbeiterin oder Mitarbeiter. Die Dissertation nutzt das Framework von Matt et al. (2019)[1], um die Inhalte und Forschungsziele zu strukturieren und einzuordnen.

Ziel dieser Dissertation ist es, einen Beitrag zu einem umfassenden Überblick für Organisationen zu leisten, um die Individuen im Zuge der Digitalisierung zu verstehen. Dabei wird untersucht, welche Bedenken ihre Kundinnen und Kunden in Bezug auf digitale Technologien haben, welche Gestaltungsmöglichkeiten sie haben, um diese Bedenken zu adressieren, und wie es das Verhalten von Kundinnen und Kunden beeinflusst. Dadurch können sie das Potenzial dieser Technologien realisieren oder ihre Schäden reduzieren. Diese Arbeit wendet eine Vielzahl an methodischen Ansätzen an (qualitative Methoden, z.B. halbstrukturierte Interviews und qualitative Inhaltsanalyse, und quantitative Methoden, z.B. quantitative Entscheidungsmodelle und Datenerhebung aus Online-Fragebögen). Damit

[1] Matt, C., Trenz, M., Cheung, C. M. K., & Turel, O. (2019). The digitization of the individual: Conceptual foundations and opportunities for research. Electronic Markets, 29(3), 315–322.

liefert die Dissertation neue Erkenntnisse für Organisationen, um digitale Technologien besser zu implementieren, indem sie die Konsequenzen für Individuen und das Verhalten von Individuen betrachtet.

Um erstens einen Beitrag zum besseren Verständnis der negativen Folgen, die die Digitalisierung für den Einzelnen mit sich bringen kann, zu leisten, umfasst Teil A dieser Dissertation zwei Forschungsartikel, die sich mit den Bedenken des Einzelnen beschäftigen. Die Forschungsartikel P1 und P2 zeigen in zwei unterschiedlichen Bereichen, welche Bedenken Individuen bei der Nutzung digitaler Technologien haben und was Individuen davon abhält, diese zu nutzen. P1 konzentriert sich auf diejenigen Bedenken, die bei dem Einsatz automatisierter Entscheidungsfindung in Erscheinung treten können. P2 beschäftigt sich mit den Bedenken, die Patientinnen und Patienten sowie Fachkräfte im Hinblick auf die digitale Transformation im Gesundheitswesen haben. Daher präsentiert diese Dissertation Wissen über die Ängste und Bedenken der Individuen und bietet Ansatzpunkte, um verantwortungsvolle und transparente digitale Technologien zu entwickeln.

Um zweitens einen Beitrag zu Gestaltungsansätzen für Informationssysteme zu leisten, werden in Teil B Gestaltungsansätze vorgestellt, mit denen Organisationen die wahrgenommenen Konsequenzen für Individuen adressieren und das Verhalten im Umgang mit digitalen Technologien ändern können. Diese ermöglichen es Organisationen die Kundenzufriedenheit bei der Nutzung von digitalen Produkten und Dienstleistungen zu erhöhen. Beide Forschungsarbeiten in Teil B stellen quantitative Entscheidungsmodelle als Entscheidungshilfe für Organisationen vor. P3 entwickelt ein quantitatives Entscheidungsmodell, das Organisationen in die Lage versetzt, fundierte Entscheidungen darüber zu treffen, ob bestimmte Kundinnen und Kunden in ihre Geschäftsprozesse integriert werden sollen oder nicht. Dabei wird die notwendige Kundenunterstützung berücksichtigt. P4 liefert ein formales Entscheidungsmodell für Investitionen zur Rückgewinnung von Kundinnen und Kunden. Somit bietet diese Dissertation zwei Gestaltungsansätze, die Organisationen Informationen zur Gestaltung von Informationssystemen liefern und sie dabei unterstützen, fundierte Entscheidungen bei der Einführung digitaler Technologien zu treffen.

Drittens, um zum Verständnis beizutragen, warum und wie sich Individuen auf bestimmte Weise verhalten und wie dieses Verhalten beeinflusst werden kann, wird in Teil C das Verhalten von Individuen bei der Nutzung digitaler Technologien untersucht. P5 entwickelt eine Metrik, um das Privacy-Paradoxon besser zu erforschen. Das bedeutet, die irrationale Abweichung zwischen dem tatsächlichen Verhalten von Individuen und ihren theoretischen

Bedenken bezüglich der Preisgabe ihrer privaten Informationen bei der Nutzung digitaler Technologien. Damit bietet diese Dissertation eine Grundlage, insbesondere für Forscherinnen und Forscher sowie Individuen, um unerwünschtes Verhalten bei der Nutzung digitaler Technologien zu verhindern.

Zusammenfassend lässt sich sagen, dass diese Dissertation wissenschaftliche Erkenntnisse zur Erforschung der Digitalisierung des Individuums leistet und damit ein Thema von grundlegender Bedeutung im digitalen Zeitalter behandelt. Die in dieser Dissertation entwickelten Modelle und Ansätze zeigen Wege auf, wie die Bedingungen für das digitalisierte Individuum auf allen drei Forschungsperspektiven (Folgen, Gestaltung und Verhalten) verbessert werden können.

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1 Introduction

1.1 Motivation[1]

For decades now, digitalization has become an ever more powerful engine of change in near enough all areas of our daily lives so much so that it has become virtually indispensable for individuals, organizations, and society at large (Gimpel & Schmied, 2019; Legner et al., 2017). As far as organizations are concerned, increasing digitalization often affords them valuable advantages, yet it also poses significant challenges. Digital transformation requires them not only to react quickly to changing markets but also to negotiate a constant, finely balanced recalibration of their interactions with individuals (Legner et al., 2017; Matt et al., 2019). What is more, digital technologies enrich the appeal of existing products and services, yet they also give flexible, tech-savvy organizations the precious opportunity to implement new and more lucrative business models (Legner et al., 2017; Matt et al., 2019). These digital technologies, like social media, big data, the Internet of Things, mobile computing, and cloud computing, are an integral part of many products and services and influence processes and business models in all industry sectors from autonomous cars in the automotive industry to robo-advisors in financial services (Legner et al., 2017). Digital transformation, then, has seen economies grow as digitally aware organizations have become more profitable (Hitt & Brynjolfsson, 1996; G. Lee et al., 2018).

Notwithstanding these impressive upsides to digital technologies, however, their use can also have downsides. “Dark side of IT” has become a familiar term and research has already turned its focus on the negative effects of IT use (D’Arcy et al., 2014; Tarafdar et al., 2015). Kim et al. (2011) developed a taxonomy to deal with the malicious use of the Internet, such as spam, malware, hacking, or violation of digital property rights. Meanwhile, Pirkkalainen and Salo (2016) reviewed two decades’ worth of dark side research and identified four types of negative effects: technostress, information overload, IT addiction, and IT anxiety. Gimpel and Schmied (2019) looked at the risks and side effects of digitalization to develop a taxonomy of the adverse effects of IT use. In a literature study, Vial (2019) showed that value creation through digital transformation has positive as well as negative ramifications for organizations. These

[1] Since it is in the nature of a cumulative dissertation that it consists of individual research papers, this section as well as the last Section 5 partly comprise content taken from the research papers included in this thesis. To improve the readability of the text, I omit the standard labeling of these citations.

adverse side effects can occur at multiple levels, be it the individual, the organizational, or the societal.

Digitalization affects individuals and is not limited to the organizations' borders (Matt et al., 2019). Individuals make their own decisions about which technologies they use, and about when and how they use them. In doing so, they are responsible for the costs of those technologies and their use (Matt et al., 2019). At the individual level, digitalization has become a key issue since the exponential rise of new technologies and the constant development of existing technologies have created heavily digitized individuals (Matt et al., 2019). Many have become willing to adopt new digital technologies that might improve their private lives, and yet there is a long list of concerns due to unclear benefits and unknown risks (D'Arcy et al., 2014). As IT becomes ever more intelligent, networked, and ubiquitous, the use of digital technologies may have unexpected, unintended, and unfortunate effects for individuals (Gimpel & Schmied, 2019). Indeed, extensive use of digital technologies can have far-reaching consequences for individuals, such as technostress, privacy loss, digital overload, or addictive behaviors (Legner et al., 2017; Matt et al., 2019). Even if digitized individuals enjoy various advantages (e.g., improved health, increased motivation, or improved quality of life), researchers and organizations should look beyond the obvious positive effects, since the hazards associated with digital technologies may have a deep and long-lasting impact on individuals (Matt et al., 2019).

The digitalization of the individual should also be taken into account by organizations and requires new research efforts as the interactions between individual customers and organizations have changed significantly (Matt et al., 2019). New digital technologies impact more than decision-making and have a massive impact on individuals' behavior because they now have unprecedented information access and communication capabilities (Chanias, 2017; He et al., 2017; Hong & Lee, 2017; Vial, 2019). The literature to date has already provided first comprehensive approaches that consider the afore-mentioned organizational, individual, and social levels of this phenomenon, yet there remains a sizeable gap in the research on the dynamic process of digitalization (Majchrzak et al., 2016; Newell & Marabelli, 2015; Vial, 2019). Matt et al. (2019) have made the valid point that we need a better understanding of how the behaviors of individuals are affected by digital technologies, how customers demand change, and how the purchasing process of organizations has to be adapted to create more value for organizations and individuals.

To be economically successful, organizations would do well to adapt their customer relationship management (CRM) to the changing needs of digitized individuals (Leußer et al., 2011). This means that all corporate activities ought to be given a comprehensive, value-oriented focus on the customer, with a view to coordinated and adequate marketing, sales and service concepts, and the targeted use of information technologies (Gneiser, 2010). In doing so, they should take into account the various phases of the customer relationship lifecycle (e.g., customer acquisition, customer retention, or customer recovery), different interaction channels (e.g., personal visits, video advisory, social networks, or automated product recommendations), different instruments (e.g., quality, complaint, or service management), and different customer segments (e.g., grouped by customer needs or technology acceptance) (Bruhn, 2016; Leußer et al., 2011). As digital products and services take an increasing market share, organizations can collect, process, and share ever more customer data (Karwatzki et al., 2017). This individual customer data is of essential importance to make better decisions and achieve CRM objectives throughout the customer relationship lifecycle (Reimer & Becker, 2015). For customers, however, this wealth of data can come at the price of unintended consequences (Karwatzki et al., 2017). To mitigate those, organizations cannot use customer data for their analytics and decision-making without fully understanding the negative as well as the positive consequences for customers as individuals (He et al., 2017; Matt et al., 2019). To be clear, the digitalization of the individual calls for a coherent and elaborate approache on the part of organizations and researchers in order to advance their understanding of digitized individuals and help to exhaust the full benefits of digitalization are available in all applications and contexts while the associated risks are mitigated (Matt et al., 2019).

1.2 The roles and perspectives of individuals in a digital world

Digitalization extends beyond the boundaries of organizations to the point at which it affects individuals (Matt et al., 2019). Matt et al. (2019) present a holistic research framework with different research perspectives on the digitalization of the individual (see Figure 1.2-1). The latter causes different behaviors and consequences for individuals, and as such it requires new views on technological design. The various research perspectives presented here offer a comprehensive understanding of digitized individuals, which helps organizations to analyze their customers as individuals. As will become evident in the following pages, the framework shows that a digitized individual can take on different roles, be it that of the individual itself, the citizen, the social being, the customer, or the employee. Using this framework, researchers can classify and precisely delineate this research area of the digitalization of the individual in a structured way.

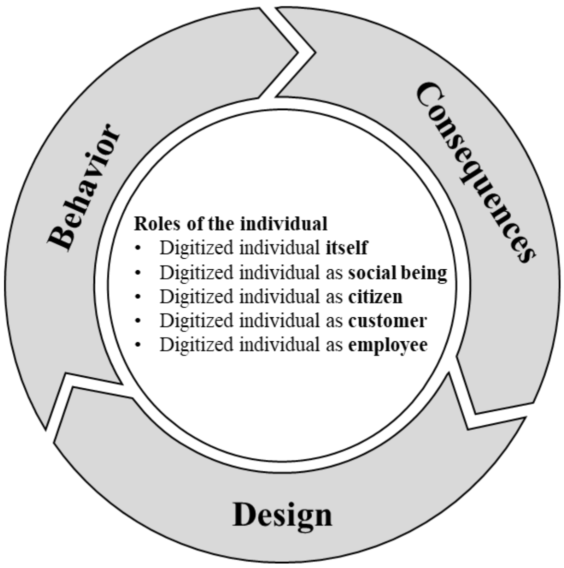

Figure 1.2-1 Roles of the individual and research perspectives (Matt et al., 2019)

In general, digitalization refers to the sociotechnical phenomena and processes of adopting and using digital technologies and media (Legner et al., 2017). In detail, digital technologies and media are "all the electronic devices (hardware) and applications (software) that use information in the form of numerical codes (usually binary codes), as well as all the media (i.e., means and channels of general communication in society) that are coded in formats that can be processed by these devices and applications" (Gimpel & Schmied, 2019, p. 4). Matt et al. (2019, p. 315) define the digitalization of the individual "as the proliferation of digital technologies in the lives of individual users." It is worth noting that, according to this definition, individuals decide for themselves which technologies they use, and when and how they use them. Furthermore, they are responsible for the consequences of their usage (Matt et al., 2019). Upon deeper consideration, however, the individual acts in several simultaneous roles when using digital technologies, namely that of the individual itself well as that of the social being, the citizen, the customer, and the employee (Matt et al., 2019; Vodanovich et al., 2010). These different "roles of the individual describe the different spheres in which the digitized individual acts and exerts active or passive influence" (Matt et al., 2019, p. 317). In the following section, we shall go into some detail about these different roles.

Digitalization promises several advantages for *the individual as itself*, such as more conveniences and self-determination in daily life. However, essential questions remain about technology adoption and usage and how individuals can manage the increasing complexity of their IT portfolios (Matt et al., 2019). When using digital technologies, individuals must weigh positive and negative consequences (Gimpel & Schmied, 2019; Matt et al., 2019).

Digital technologies have fundamentally changed the interaction between individuals. Ever since, *individuals as social beings* can communicate with each other via social media and online communication applications, regardless of time and place (Appel et al., 2020; Olsson et al., 2020). These new forms of communication, however, can also lead to psychological suffering and isolation since social media provide a platform for virtual bullying with dire consequences (Yao et al., 2019). Content posted on social media has a lasting legacy and can spread far and wide in no time (Yao et al., 2019). What is more, now that digital technologies are used as the standard tool for communication between individuals, more personal data is available online than ever before (Olsson et al., 2020). As a result, individuals face new challenges, first in protecting themselves against the misuse of vast amounts of personal data, and then in dealing with the consequences of said misuse.

Digitalization extends its considerable advantages to the implementation of public processes. For example, it can help shape public opinion, increase equality, and impact education, jobs, and culture (Matt et al., 2019). Nevertheless, *individuals as citizens* are vulnerable to certain dangers of digitalization in the public sector. The sources of information that citizens use to form their opinions have changed significantly over time, as social media such as Facebook and Twitter have become more powerful (Mason et al., 2018). This can have far-reaching consequences, including the spread of fake news with its detrimental impact on democracy (Mason et al., 2018).

Individuals as customers are becoming ever more important for organizations, as changing customer expectations are a powerful driver for digitalization (Urbach et al., 2019). Increasingly so, organizations are embracing new opportunities to integrate individuals into their business processes, which requires them to rethink their business models in a changing competitive environment (Legner et al., 2017). The attendant advantages for customers include changed buying behavior via new channels and devices, reduced purchasing behavior, and automatic demand analysis while executing purchases (Matt et al., 2019). Nevertheless, these data-intense services raise serious customer concerns that organizations must closely address (Karwatzki et al., 2017).

These days, digitalization affords organizations as well as employees a wide range of novel opportunities, since office work can now often be done anywhere and anytime, and frequently on an individual's private device (J. Lee et al., 2017; Messenger & Gschwind, 2016). Accordingly, *individuals as employees* have gained convenience, increased flexibility, and improved work-life balance (Messenger & Gschwind, 2016). Meanwhile, organizations have begun to profit from increased productivity and reduced expenses (G. Lee et al., 2018), and yet the digitalization of individuals as employees can also pose challenges. For instance, many individuals now have greater privacy concerns about an organization taking more control over IT (Matt et al., 2019). What is more, the increasing fusion of private and professional lives can raise an individual's stress perception, as work is no longer confined to the job environment (Sarker et al., 2018).

If the advantages of digitalization are to outweigh the negative consequences for individuals in their various roles and organizations, it is necessary to better understand how individuals perceive the consequences of digital technologies, how their behavior changes when using them, and how the design of digital technologies ought to be adapted. What follows is an explanation of the three research perspectives in Figure 1.2-1.

The first research perspective focuses on the positive and negative *consequences* of digital technologies being used in different application contexts (Matt et al., 2019). As Gimpel and Schmied (2019) have shown in their taxonomy, the adverse effects of IT use are many in number and range from shifting political control and ethical challenges to health impairment and privacy issues. To focus, for a moment, on the latter as a key issue of digitalization, more and more personal data is collected by intelligent algorithms and big data analytics, which is causing unintended privacy issues for individuals (Karwatzki et al., 2017; Matt et al., 2019).

The second research perspective provides organizations with information on how to *design* technologies to better serve digitized individuals. This research perspective includes topics such as product and service design fit for the changing expectations of individuals as well as new interaction channels between individuals and organizations (Matt et al., 2019).

The third research perspective considers the *behavior* of digitized individuals and "aims at an understanding of why and how individuals behave in certain ways and how this behavior can be influenced" (Matt et al., 2019, p. 317). To gain a deeper understanding of how individual behaviors are affected by digital technologies, researchers and organizations need to investigate subject areas such as technology adoption by individuals (in their role as individuals themselves), social interactions of individuals (in their role as social beings), and purchase behavior of individuals (in their role as customers) (Matt et al., 2019).

It is worth noting that these three research perspectives should not be considered in isolation. Together, they form a continuous cycle in which the behaviors of individuals have certain consequences which in turn have implications on the design of digital products and services. All research perspectives thus influence one another, so the cycle can be started from all perspectives. The stated purpose of all three is to work together to realize the potential of digitalization and minimize its negative impact on individuals and organizations (Matt et al., 2019).

1.3 Aim and outline of this dissertation

At present, the literature on digital transformation is focused mainly on the organizational perspective (Vial, 2019). Nevertheless, organizations would do well not to neglect the individual perspective, since it pays great dividends to understand customer needs and how individuals are affected by digital technologies (Matt et al., 2019). What this calls for is a comprehensive understanding of how digital technologies extend beyond the boundaries of the organization into the individual context (Matt et al., 2019; Vial, 2019). With that in mind, this dissertation aims at contributing to an emerging overview for organizations to understand their customers' concerns about digital technologies, which design options are available to organizations to address these concerns, and how it influences their behavior to realize the potential of digital technologies and mitigate their risks. In short, this dissertation provides organizations with novel insights on how to better implement digital technologies by regarding the individual perspective. The framework used in the following pages is that of Matt et al. (2019), which is designed to structure and classify the research objectives of Figure 1.2-1. The dissertation covers the three research perspectives outlined above and focuses on the individuals' roles as themselves and as customers.

Table 1.3-1 provides an overview of the structure and the research articles included in this dissertation. Part A deals with the negative consequences of the digitalization for the individual (P1 and P2). Part B examines design approaches of technologies in organizations (P3 and P4). Part C analyzes the behaviors of individuals in a digital world (P5). And lastly, this table also presents titles, objectives, research methods, co-authors, and publication outlets of all research articles.

Table 1.3-1 Research overview of the dissertation

Part A: Negative consequences of the digitalization for the individual				
No.	**Research paper title**	**Objective**	**Method**	**Co-Authors**
P1 (Ch. 2.1)	Fear of algorithms: A synopsis of concerns about automated decision-making	Identifying, structuring, and communicating individuals' concerns about ADM for improving ADM-related offers and services that consider individuals' perspectives	Qualitative content analysis	Bayer, Sarah; Schmied, Fabian
P2 (Ch. 2.2)	Individual concerns associated with the digital transformation in healthcare: Professionals' and patients' hindrances to adopt digital healthcare services	Providing a framework that explains individuals' concerns and fears about the negative impacts of digital transformation in healthcare to anticipate, explain, or assess problems with the adoption of digital healthcare services	Qualitative research using techniques from the grounded theory method	Blaß, Marlene; Gimpel, Henner; Regal, Christian
Part B: Design approaches for information systems in organizations				
No.	**Research paper title**	**Objective**	**Method**	**Co-Authors**
P3 (Ch. 3.1)	Self-Services – Do not leave your customers alone with the technology[1] Published in the Proceedings of the 12th International Conference on Wirtschaftsinformatik, March 4-6 2015, Osnabrück, Germany	Developing a mathematical approach for the optimal customer integration in business processes that takes full account of the corresponding customer support to help the introduction of self-services	Quantitative decision model	Kryzhanivska, Lena; Müller, Anna-Luisa; Rupprecht, Lea
P4 (Ch. 3.2)	Between death and life – a formal decision model to decide on customer recovery investments[2] Published in Electronic Markets (2018) 28: 423–435.	Proposing a formal decision-making model on whether or not to invest in customer relations to improve customer recovery and reduce companies' customer recovery costs	Quantitative decision model	Kleindienst, Dominikus
Part C: Behavior of individuals in a digital world				
No.	**Research paper title**	**Objective**	**Method**	**Co-Authors**
P5 (Ch. 4.1)	The disclosure of private data: Measuring the privacy paradox in digital services Published in Electronic Markets (2018) 28:475–490	Development of a privacy paradox metric that aggregates consumers' privacy intentions and behavior to a single measure and quantitatively assesses the extent of paradoxical privacy behavior on the part of consumers in the context of digital services	Metric development using design science	Gimpel, Henner; Kleindienst, Dominikus

[1] Please note that this research paper was published under my maiden name "Engel." In the meantime, my surname changed to "Waldmann."
[2] Please note that I was the lead author of this research paper.

Part A: Negative consequences of the digitalization for the individual

Part A of this dissertation addresses the negative consequences of the digitalization for the individual. It includes two research articles that examine the concerns of individuals. P1 focuses on those to do with the use of automated decision-making (ADM). P2 takes a closer look at the concerns that patients and professionals have about the digital transformation in healthcare. Thus, whereas P1 reviews the issue in general terms, P2 gives a more detailed insight into a specific context.

P1 examines concerns of individuals about the use of ADM. In the course of digitalization, the impact of ADM and algorithms are spreading far and wide , as decision-making is no longer determined by humans alone but already supported by technology or indeed entirely replaced by algorithms (Diakopoulos, 2016; Martin, 2019; Wachter et al., 2017). The use of algorithms promises a wide range of benefits, as they can analyze extensive amounts of data to make predictions at a level of accuracy unattainable for any human being (Martin, 2019; Power, 2015; Strobel, 2019). However, algorithms can also have significant negative consequences for individuals. Since the concerns about those consequences might inhibit the adoption of ADM, a broad overview is necessary. The overview might help to address the individuals' concerns to support the implementation of ADM applications and enable individuals to be better informed about potential risks. P1 identifies, structures, and communicates the context-independent concerns many individuals have about ADM. The method used for this purpose is a structured literature review and a qualitative content analysis of semi-structured interviews. The overall framework could serve as a basis upon which organizations can develop transparent ADM-related products and services, all while dealing with the concerns of individuals in a responsible manner. P1, then, addresses the following research question:

Which concerns do individuals have about the use of automated decision-making?

Digitalization plays a significant role in the healthcare sector and e-Health has proven itself to be an efficient healthcare instrument. The level of acceptance among healthcare professionals and patients, however, is relatively low. To examine the reasons for this, P2 develops a framework for the concerns many individuals have about adverse outcomes of digital transformation in healthcare. The methodology applied here is based on the Grounded Theory Method, including interviews with patients and healthcare professionals. E-Health will not be implemented successfully, nor will the adoption of digital health services be expedited, until the reservations of patients and professionals are fully understood and overcome. Therefore, P2 centers on the following research question:

Which factors can hinder an individual's intention to use digital technologies in healthcare?

Part B: Design approaches for information systems in organizations

Part B presents various design approaches for information systems that enable organizations to increase customer satisfaction with digital products and services. What this requires is a focus on the individual perspective, and this is of further interest to organizations seeing as digitalization has given them new opportunities to integrate customers into their business and value creation processes (Cheung et al., 2014; Libo Liu et al., 2016). The purchase behavior of individuals is constantly changing, but given the wide variety of new communication channels and devices, individuals can be (partially) integrated into tasks previously performed by organizations. P3 develops a quantitative decision model that enables organizations to make informed decisions on whether or not to integrate certain customers in their business processes, all while accounting for the necessary customer support. What is more, digitalization increases market transparency, which allows customers to get a better overview of products and services than ever before. As a result, switching between different providers becomes almost effortless. To show how to counteract this behavior, P4 provides a formal decision model on customer relation recovery investments.

Customer support has become an essential factor of a company's competitiveness (Negash et al., 2003). Integrating customers in business processes, however, is somewhat problematic, since not all of those processes lend themselves to integration and it is uncertain how customers will react to self-services. Consequently, organizations ought to consider whether or not a customer needs support, and this consideration is facilitated in the pages of P3. In it a quantitative decision model is developed to answer the question of whether or not to integrate customers into business processes all while considering the economic effect of the corresponding customer support. This decision is predicated on the change in cash flow which in turn is predicated on the introduction of self-service. On the one hand, customer support generates costs. On the other hand, however, it has a positive impact on service quality and customer satisfaction, which means it also has a positive impact on the economic value of a customer, especially with a view to the resultant increase in the customer's acceptance of the self-service technology (Anselmsson, 2001; Reinders et al., 2008). The applicability of this model and its practical benefit are illustrated by a case study. P3, then, answers the following research question:

In which business processes should customers be integrated when considering the necessary extent of customer support?

P4 develops a formal decision model that computes the threshold at which investing in an individual customer relation is economically viable by considering the probability of a customer relation being "alive," "dying," or "dead." With digitalization, customer migration is easier than ever before and individuals show a growing willingness to make the switch due to increasing market transparency and rising impersonality (Desai, 2014; Leußer et al., 2011). Many organizations neglect customer recovery as they focus on customer acquisition and retention. As a result, they lose a large part of their revenue when their customers defect (Griffin & Lowenstein, 2001). With the help of customer recovery management, an organization can win back customers who have explicitly terminated the business relationship or implicitly done so by taking their custom elsewhere (Leußer et al., 2011). Accordingly, the research question of P4 is:

How can an organization decide whether or not to invest in a customer relation on the basis of the probability that the customer relation is "dying"?

Part C: Behavior of individuals in a digital world

In part C, this dissertation investigates the third research perspective presented in Figure 1.2-1, i.e., behavior. In the course of digitalization, individuals can encounter adverse consequences. An organization can address these by refitting its digital products and services with customized designs that account for changes in the behavior of individual customers. However, the behavior of individuals is not always rational since individuals are endowed with bounded rationality and often act without having essential information at hand (Keith et al., 2012). What is more, the rise of digital technologies makes an ever greater amount of personal data available and thus increases their users' privacy concerns. Hence, privacy is an important topic for individuals as well as for organizations and one that cannot be ignored when examining the downsides of digitalization. Therefore, P5 deals with non-rational privacy behavior. Individuals may often claim that they want to protect their privacy, and yet many behave as though the opposite were true (Acquisti, 2004). This irrational behavior is called the privacy paradox (Norberg et al., 2007). P5 develops a privacy paradox metric (PPM) that aggregates and quantifies in a single measure the deviation between the privacy intentions and privacy behaviors of individuals. Organizations will then be able to use this metric to identify the unintentional data release of a customer and manage the associated risks. As the first quantitative measure of the privacy paradox, the PPM may have several benefits for companies that provide digital services as well as for ICT platform providers, consumer protection organizations, consumers themselves, and researchers. The design science research methodology is used to contribute to a design theory by answering the following research question:

How can the privacy paradox metric, which aggregates the privacy intentions and privacy behaviors of consumers into a single measure, be quantified for digital services?

In summary, Figure 1.3-1 presents a detailed outline of this dissertation. Chapter 1 provides an introduction. Chapter 2 analyses the dire consequences that customers fear when using automated decision-making (Chapter 2.1) and digital health services (Chapter 2.2). Chapter 3 presents design options to address such concerns by first determining the necessary extent of customer support when integrating customers into business processes (Chapter 3.1), and then by introducing a decision model that makes it possible to decide on the right customer recovery investments (Chapter 3.2). Chapter 4 provides a detailed insight into the behavior of individuals and discusses the privacy paradox, i.e., the divergence between stated privacy attitudes and actual behavior. And finally, Chapter 5 discusses the results, provides an outlook for future research, and offers the dissertation's overall conclusion.

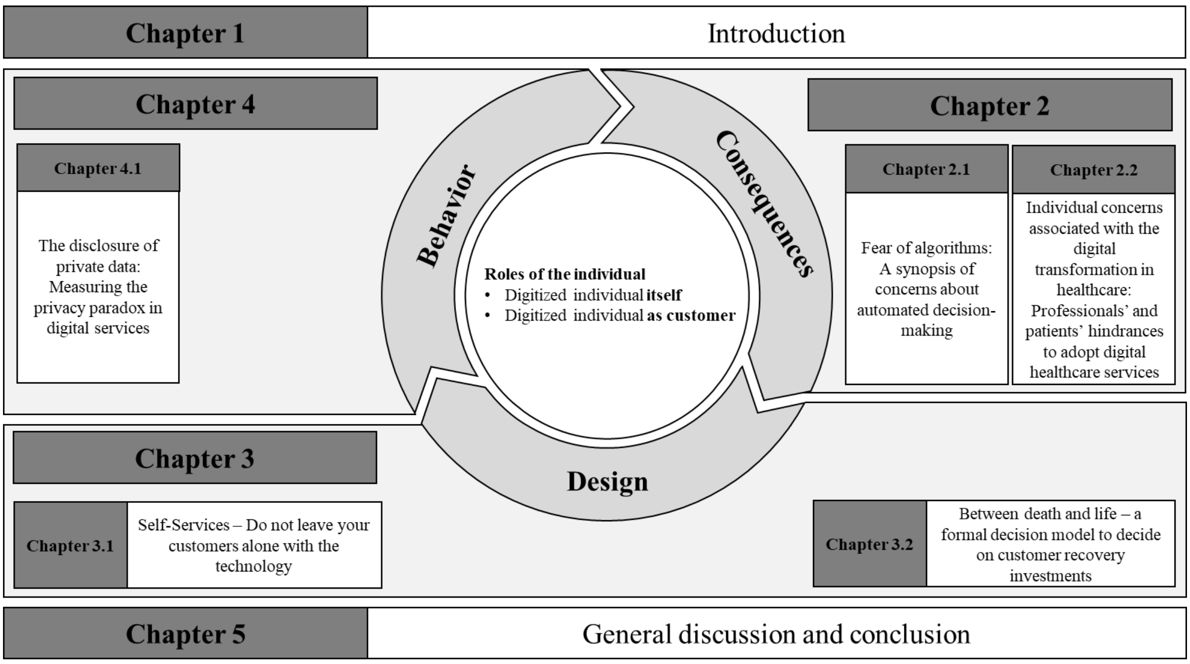

Figure 1.3-1 Structure of this doctoral dissertation

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2 Part A: Negative consequences of digitalization for the individual

2.1 Fear of algorithms: A synopsis of concerns about automated decision-making

Abstract

Automated decision-making (ADM) is making its impact in all areas of modern life. Decisions previously made by humans are increasingly supported or replaced by algorithms. Many people harbor reservations about ADM, and yet, there is no exhaustive study that structures these concerns. The objective of our research is to outline a comprehensive framework of concerns about ADM. Based on a structured review of the literature and a qualitative content analysis of semi-structured interviews, we identified ten major concerns regarding the underlying technology, data, or the decision itself. Furthermore, we identified 14 concerns about the potential consequences of using ADM. Our framework is intended to guide future research on concerns about ADM, while also serving as a touchstone for anyone developing ADM-related offers and services that account for the potential reservations of the intended user group.

Keywords: Algorithm, Automated decision-making, Algorithmic decision-making, Concerns

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Status:

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2.1.1 Introduction

Algorithms are “a sequence of computational steps that transform inputs into outputs, and range from simple if-then statements to artificial intelligence (AI), machine learning, and neural networks” (Martin, 2019). Nowadays, algorithms are involved in all areas of life, for instance by producing news articles based on structured data, by supporting recruitment processes, by detecting fraud in sports betting, by deciding which physicians see which patient, and by defining dynamic prices in many application areas, such as e-commerce (e.g., Amazon), tourism (e.g., Airbnb), and transportation (e.g., Uber) (Diakopoulos, 2016; Martin, 2019; van den Broek et al., 2019). In some of these areas, we see “complex and networked algorithms that are beyond proper human understanding and control” (Gimpel & Schmied, 2019, p. 8). This comes with certain adverse, unexpected, and unintended effects (Gimpel & Schmied, 2019; Majchrzak et al., 2016), and these effects – positive as well as negative – are extending their reach into all aspects of modern life (Diakopoulos, 2016). Decision-making processes previously made by humans are increasingly supported (augmented by technology) or even replaced by algorithms (fully automated) (Martin, 2019; Wachter et al., 2017).

In the future, algorithms are expected to gain even more influence due to an ever-increasing degree of automation in decision-making processes as well as the expansion of application areas of ADM. This is affecting individuals, organizations, and society at large. On the one hand, organizations and public authorities may benefit from the accuracy, scale, speed, simplicity, and cost-efficiency of automated decisions (Diakopoulos, 2016). There are those who argue that algorithmic decisions foster objectivity and fairness (van den Broek et al., 2019). Others predict that algorithms may have significant negative consequences for individuals affected by automated decisions. Two prime examples are when potentially biased algorithms support policing (known as predictive policing) or assist judicial decision-making in court (Angwin et al., 2016; Binns et al., 2018; Corbett-Davies et al., 2016; Dressel & Farid, 2018; Martin, 2019). Algorithmic decisions are further criticized for facilitating other ethical violations such as sexism or privacy invasions (van den Broek et al., 2019). In this paper, we focus on reservations that individuals harbor about ADM.

Prior literature has already investigated potential risks and side effects of ADM for individuals, such as discrimination, lack of data protection, unfairness, or wider ethical issues. Most research articles discussed these issues in highly specific (and primarily future-oriented) use cases. However, there is no comprehensive overview of the chief concerns held by individuals when dealing with ADM, which is a necessary foundation to improve ADM adoption. What is missing, therefore, is a synopsis of these concerns about ADM derived from literature (focused mainly on specific single use cases) and complemented with a survey of multiple ADM cases. To fill this gap in the research and to provide a starting point for further, detailed research about these concerns, we aim to answer the following question:

Which concerns do individuals have about the use of automated decision-making?

The overview we have generated in reply to this question may serve as a foundation upon which others can develop responsible and transparent ADM-related offers and services with full regard for the fears and reservations of those affected (Diakopoulos, 2016). Furthermore, we intend to summarize as well as extend existing research to offer a basis for future research.

The paper is structured as follows: The following section provides the theoretical background for algorithmic decision-making and concerns. Then, we describe the methodological approach of our structured literature search and the qualitative content analysis of our semi-structured interviews, followed by the presentation of results. After the result section, or discussion includes practical and theoretical implications, and an outlook towards future research, followed from the conclusion.

2.1.2 Theoretical background

To understand concerns about ADM one must first dive deeper into the negative aspects of IT. Although there is an apparent pro-IT bias in information systems (IS) research, there is also research on the "dark side of IT." The *Information Systems Journal* published two consecutive special issues on the dark side of information technology use (Tarafdar et al., 2015a, 2015b). These special issues comprise articles that focus on one negative aspect of IT use at a time, such as technostress, IT interruptions, computer abuse, IT-mediated control, or unauthorized file sharing (Tarafdar et al., 2015a, 2015b). Further, Pirkkalainen and Salo (2016) review 37 articles in the AIS Senior Scholars' Basket of Journals and detect four types of dark side phenomena: information overload, IT addiction, and IT anxiety. Kim et al. (2011) provide a taxonomy of the dark side of the Internet and focus on attacks, costs, and appropriate responses. They identify technology-centric dark side effects like spam, malware, hacking, and digital property rights violations. Additionally, they identify non-technology-centric dark side effects such as online theft, cyberbullying, and the aiding and abetting of crime. Gimpel and Schmied (2019) aim to provide a broad overview of dark side phenomena by developing a taxonomy of the most severe risks and side effects of digitalization, such as adverse exchange, adverse economic shifts, impairment of health, undesirable behavioral adaptation, or losing control over algorithms. Some of those dark sides of IT also relate to the use of algorithms.

ADM takes place when a result, e.g., a recommendation or a purchase, is achieved without human intervention (Allen & Masters, 2020). Thus, ADM is either supported by modern information and communication technologies (ICTs) or the decision is entirely made by the application of specific algorithms (Allen & Masters, 2020). This is why ADM is also called algorithmic decision-making. Another way to achieve ADM, however, may be to use complex artificial intelligence (AI) supported and trained by machine learning (ML) (Allen & Masters, 2020). Within AI, the different analytical techniques, such as descriptive, predictive, or prescriptive analytics, facilitate ever greater intelligence and business efficiency. Whereas descriptive and predictive analytics require a human manager to interpret the results, prescriptive analytics enables ADM (Vahn, 2014). In other words, it goes beyond predicting future results by anticipating what will happen, when it will happen, and why it will happen. What is more, it gives recommendations that benefit from those predictions (Kumar, 2015; Shankararaman & Gottipati, 2015). Consequently, prescriptive analytics answers the question "How can we make it happen?" (Shankararaman & Gottipati, 2015).

The impact of ADM on the lives of individuals triggers certain concerns about ADM. According to Lowry et al. (2011), we define concerns in use cases of ADM as the extent to which a person worries about possible risks and consequences associated with ADM use. The existing literature has already discussed the concerns some individuals have about ADM, e.g., discrimination (Strobel, 2019), or data privacy (Newell & Marabelli, 2015). It has also discussed factors that inhibit ADM adoption, e.g., control (Dietvorst et al., 2018) or trust (Castelo et al., 2019). It has further discussed a variety of use cases for ADM, e.g., automated travel planning (Cho & Han, 2019), autonomous driving (Dietrich & Weisswange, 2019), or automated purchases (Ringe et al., 2019), and the literature has also already discussed the implementation of ADM in business use cases (Dwivedi et al., 2021). However, these discussions have typically been grouped around single concerns, and most of the studies have focussed on a specific context. A comprehensive overview of concerns that might inhibit ADM adoption does not yet exist. In this paper, we argue for the need of a better understanding of how individuals perceive the impact of using ADM in daily life. This is necessary if we are to gain a deeper insight into the relationship between the perception of ADM's use, the perception of the consequences of ADM's use, and actual behavior, because organizations need to know which consequences individuals fear and how to address those negative perceptions (Karwatzki et al., 2017).

Further areas of academic research, such as data privacy, has indicated that individual concerns can be manifold (Hauff et al., 2015; Smith et al., 1996). Smith et al. (1996) have identified seven major data privacy concerns of customers (including data collection, secondary use, or improper access). Hauff et al. (2015) have investigated how perceived privacy-invasive data collection and usage can affect individuals. Their research has shown that, for some individuals, there are concerns at different levels. Meanwhile, Karwatzki et al. (2017) have developed a categorization of how individuals perceive the consequences of access to their personal information. This categorization spans seven types of consequences: psychological, social, career-related, physical, resource-related, prosecution-related, and freedom-related. Nevertheless, this research has merely discussed data privacy concerns (e.g., regarding unauthorized access to individuals' information), which we believe to be only one type of concern about ADM. As such, the existing research does not provide a comprehensive overview of potential concerns.

2.1.3 Research methodology and approach

To answer our research question, we take a two-step approach by way of a structured literature search and a qualitative content analysis of semi-structured interviews. First, we reviewed the existing (IS) literature to identify concerns about ADM. In so doing, we also identified current use cases for ADM, which served as a basis for the semi-structured interviews conducted in the second step. We used a search string, combining "automated decision" with the most common synonym used in the literature ("algorithmic decision"), as well as the term "prescriptive analytics," which is used primarily in the research area of statistics. Furthermore, we linked those expressions with "concern" and synonyms for concern commonly used in the literature, which yielded the following search terms: *("automated decision" OR "algorithmic decision" OR "prescriptive analytics") AND ("concern" OR "risk" OR "attitude" OR "danger" OR "aversion")*. As advised by Webster and Watson (2002), we did not restrict our literature search to databases with a focus on the IS discipline (covered by the databases ACM Digital Library and AIS Electronic Library). Instead, we expanded our search to general databases so as to cover a wide range of different research areas with our main focus directed at the domain of electronic commerce and computer science, engineering, law, marketing, logistics, and beyond (covered by the databases Science direct, EBSCOhost, JSTOR Library, SpringerLink, ProQuest). Since ADM is frequently embedded in highly topical discussions about AI, we included news from associations and academic journals. The structured literature search resulted in 175 articles. After the initial screening of titles and abstracts, the full texts of the remaining 30 articles were examined, whereupon 18 articles were classified as relevant.

An article was considered relevant if the following two conditions were met: (1) the article dealt with ADM in general or in a specific use case and (2) the article named or explained concerns or adverse effects of ADM for a specific use case or in general terms. With regard to those 18 articles, we highlighted words or phrases expressing concerns about ADM (e.g., “discrimination” (Strobel, 2019), “computer implementation may be incorrect” (Brauneis & Goodman, 2018)) and use cases for ADM (e.g., “recommender systems” (Borràs et al., 2014), “loan application” (Strobel, 2019)).

This also proved to be highly useful in preparing the semi-structured interviews, which we then conducted to identify further concerns about ADM. We chose interviewees with diverse backgrounds to cover a broad cross-section of the population in terms of age and gender as well as educational and professional backgrounds. We met the interviewees in person or spoke to them on video calls, and in each case we recorded the interview. In total, we conducted 13 interviews, as shown in Table 2.1-1.

Table 2.1-1 Demographic overview of interviewees

ID	Age	Gender	Highest educational level	Profession / Occupation
1	25	male	University degree	Student
2	60	female	High school diploma	Secretary
3	28	male	University degree	Doctoral candidate
4	34	male	Secondary school	IT administrator
5	33	female	University degree	Doctoral candidate
6	29	male	University degree	Technical employee
7	26	female	Secondary school	Nurse
8	28	male	University degree	Student
9	27	male	University degree	Doctoral candidate
10	57	male	Secondary school	Civil servant
11	57	female	University degree	Civil servant
12	22	male	High school diploma	Student
13	28	female	University degree	Doctoral candidate

After 11 interviews, the 12th did not reveal further insights of any relevance. We conducted a 13th interview anyway, but this, too, revealed nothing new. Reassured that we had reached saturation point, we determined that we had gathered enough data via interviews. The duration of each ranged from 15 to 45 minutes and comprised four steps: (1) present a definition of ADM (“decisions that are made or at least supported by algorithms”) and ensure a common understanding of ADM, (2) ask open questions about prior experiences with ADM and any associated concerns, (3) present five use cases to discuss concerns with regard to each use case, (4) present and discuss the results of our literature search.

We presented five ADM use cases (automated lending (Brauneis & Goodman, 2018), intelligent travel bots (Cho & Han, 2019), automated evaluation of applicants (Faliagka et al., 2012), autonomous driving (Dietrich & Weisswange, 2019), and automated purchases (Ringe et al., 2019). We chose those use cases because they are current in both mainstream media and academic research, and because they cover a broad spectrum of modern life, ranging from consumption, travel and locomotion, to the professional environment. Furthermore, we attached importance to the fact that the cases represent current progress as well as future scenarios. We provided the interviewees with images and a short description of these use cases. We transcribed all interviews verbatim in order to conduct a qualitative content analysis in line with the eight steps proposed by Schreier (2013). These eight steps bring together the best of various approaches to a thorough qualitative content analysis (Boyatzis, 1988; Hsie & Shannon, 2005; Mayring, 2010; Rustemeyer, 1992). We used the software MAXQDA to code the interviews, and each step of this methodology is outlined in detail below.

(1) Deciding on a research question: Our research question was defined ahead of the interviews (cf. Section 2.1.1).

(2) Selecting material: We conducted semi-structured interviews, each of which was fully transcribed. As our interview sample includes two different types of stakeholders (students and doctoral candidates involved in ADM research as well as individuals without professional experience in ADM), we chose two interviews from each group in order to set up the coding frame.

(3) Building a coding frame: To build main categories ("structuring") and generate the subcategories ("generating"), we combined a concept- and data-driven approach. Since our ultimate aim is to analyze concerns about ADM, the main category of the coding frame is *concerns about ADM*. In the following, where we only use one main category, we also refer to categories on the second level as main categories, while categories on the third level are called sub-categories. The results of our literature research were used to generate certain main- and sub-categories in a concept-driven way (e.g., technology, data and societal as main categories, as opposed to privacy incidents, discrimination and job loss as sub-categories). Furthermore, we adopted the strategy of subsumption as proposed by Mayring (2010) for data-driven categories: We reviewed the interview transcripts until we encountered a relevant aspect, then checked whether this aspect is already covered by a category and either attributed the aspect to the existing category or created a new category (e.g., organizational for main categories, as opposed to lack of enjoyment and lack of spontaneity for subcategories).

As advised by Schreier (2013), our coding frame meets the requirements of unidimensionality (our main categories are unidimensional), mutual exclusiveness (sub-categories within one main category are mutually exclusive), and exhaustiveness (all relevant aspects of the material are covered by a category). After the definition of the coding frame, we defined each category (Schreier, 2013). Subsequently, we examined the bigger picture of the coding frame, then merged and split a few categories, and refined our definitions.

(4) Segmentation: As suggested by Schreier (2013) we divided our material into segments. Since the use cases of ADM mentioned in the interviews are suitable to specify the start and the end of a unit, we chose the use cases as a thematic criterion for segmentation.

(5) Trial coding: In the next step, we applied the coding frame to further interview transcripts. We split the material among the researchers and each researcher coded the material twice within two weeks.

(6) Evaluating and modifying the coding frame: We evaluated consistency and validity. Less than 10% of codes were assigned to different categories in two coding rounds. We discussed the respective categories and revised each definition. As we did not have any leftover categories but managed to assign each code to a proper category, we determined our coding frame to be valid. See Table 2.1-3 and Table 2.1-4 for the coding frame.

(7) Main analysis: We coded the rest of the interviews, and due to the high validity and consistency, there was no need to double-code the rest of the material (Schreier, 2013).

(8) Presenting and interpreting the findings: Below, we present our framework in visual terms alongside explanations of the categories of concerns in Table 2.1-3 and Table 2.1-4. Additionally, we explain each category, illustrated by quotes in the following section.

2.1.4 Results

With the help of our structured literature search and semi-structured interviews, we identified 24 concerns. 13 concerns resulted from the structured literature search, 22 from the semi-structured interviews, which is to say that eleven emerged from both sources. Figure 2.1-1 structures the 24 concerns. We divided the framework into two categories of concerns: On the left-hand side of the chart, we identify concerns inherent to technology, data, or decisions. Those concerns do not necessarily have a direct impact but can develop into graver concerns about the consequences on the right-hand side.

Since applied technology, such as an algorithm, needs data to make automated decisions for the user, the concerns on the left-hand side of the framework are divided into three categories:

technology, data, and decision. These concerns about technology, data, and decision can lead to further concerns in different categories adapted from Karwatzki et al. (2017) and described in Table 2.1-2.

Table 2.1-2 Categories of concerns about consequences that individuals have due to the use of ADM adapted from Karwatzki et al. (2017)

Category	Definition
Physical	Loss of physical safety due to the application of ADM
Social	Change in social status due to the application of ADM
Resource-related	Loss of resources due to the application of ADM
Psychological	Negative impact on one’s peace of mind due to the application of ADM
Prosecution-related	Legal actions taken against an individual due to the application of ADM
Career-related	Negative impacts on one’s career due to the application of ADM
Freedom-related	Loss of freedom of opinion and behavior due to the application of ADM

A concern on the left-hand side can give rise to more than one concern on the right-hand side. For example, *“poor decision quality”* can lead to various specific concerns at different levels on the right-hand side of the framework, e.g., *“negative financial impact”* if the algorithm opts for more expensive consumer goods, *“negative physical impact”* if the autonomous driving car gets involved in an accident, or *“discrimination”* if the algorithm discriminates females for job offers. With the icons in Figure 2.1-1, we indicate whether a concern originates from semi-structured interviews (microphone) and/or from the literature review (book).

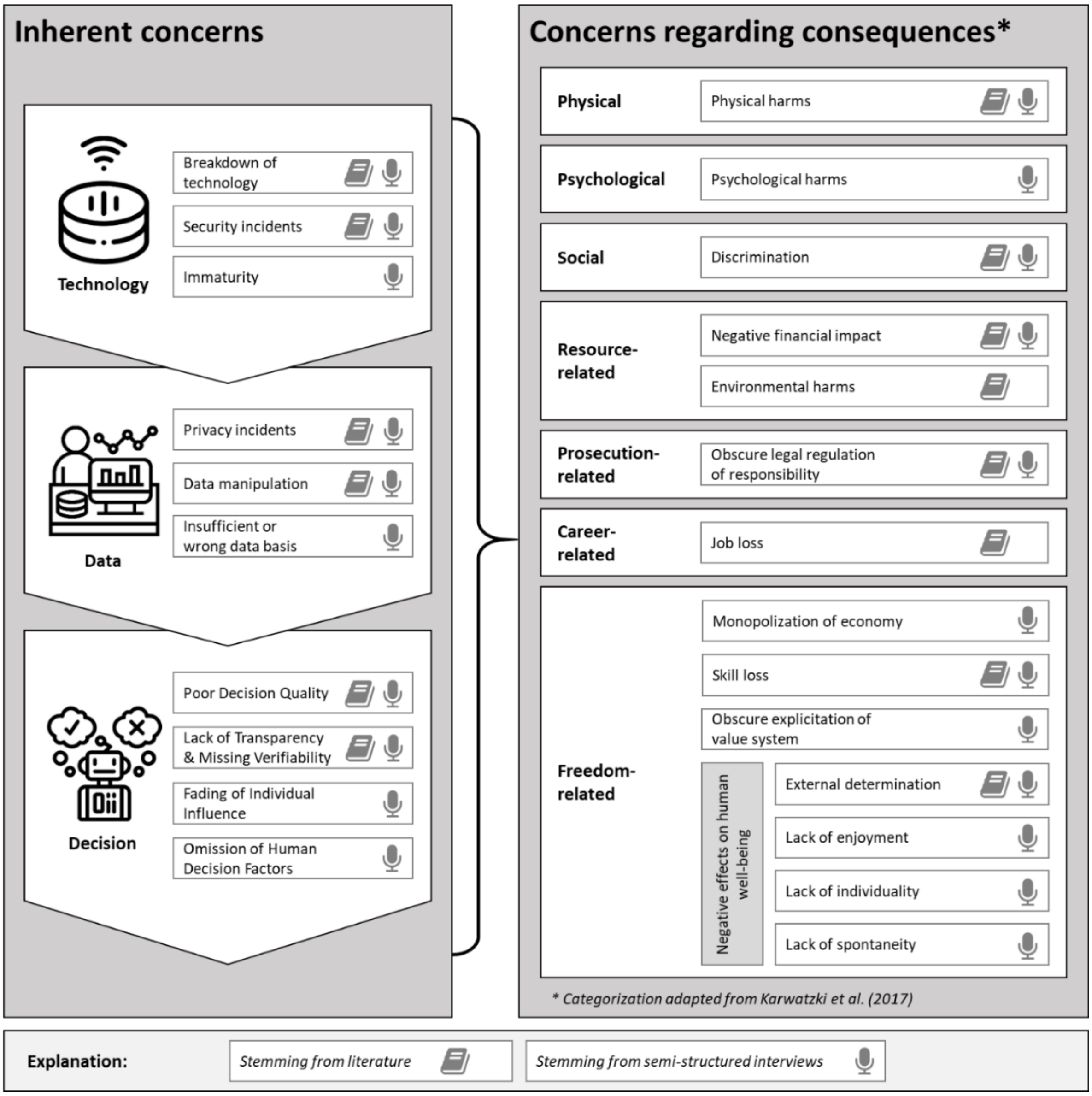

Figure 2.1-1 Framework of concerns about the use of ADM

Job loss and *environmental harms* are the only two aspects that did not occur in any interview but solely in the literature. All other 13 concerns that we found in the literature were confirmed in the interviews. Furthermore, our interviews added four concerns to the framework's left-hand side and seven concerns to the right-hand side. Table 2.1-3 presents the inherent concerns (left-hand side of Figure 2.1-1). Table 2.1-4 presents the concerns about consequences (right-hand side of Figure 2.1-1). For each concern, an explanation is provided, and literature sources as well as the IDs of the respective interviewees are shown to identify the origin of each concern.

Table 2.1-3 Individuals' inherent concerns about ADM

Concerns	Description	Literature sources	Interviews
Technology			
Breakdown of technology	*Concerns about failures in technology or single features of technology*	Winters (2017); Woldeamanuel and Nguyen (2018)	5, 10
Security incidents	*Concerns about security incidents via technology or enabled by technology, such as misuse of related IT systems*	Winters (2017); Woldeamanuel and Nguyen (2018)	4, 5, 13
Immaturity	*Concerns that technology is not yet fully mature and does not meet functional expectations*	-	2, 6, 7, 8
Data			
Privacy incidents	*Concerns about data privacy, in particular the use of and access to personal data (privacy invasion), disclosure of personal data to third parties (e.g., employers and health insurance companies), misuse of personal data for other purposes, and loss of control over the usage of personal data*	Alawadhi and Hussain (2019); Coudert (2010); Duarte (2017); Newell and Marabelli (2015); Winters (2017); Woldeamanuel and Nguyen (2018)	1, 6, 7, 8, 9, 10, 11, 12, 13
Data manipulation	*Concerns that manipulated data underlying the algorithm may lead to biased results of ADM*	Winters (2017); Yang et al. (2018)	1, 5, 9
Insufficient or wrong data basis	*Concerns that the data basis is insufficient, or that the data provided cannot be explained adequately*	-	3, 4, 6, 9, 10, 13
Decision			
Poor decision quality	*Concerns about the poor decision-making quality of a given system, leading to mistakes or decisions that do not match the fears, wishes, and preferences of individuals*	Bahner et al. (2008); Brauneis and Goodman (2018); Strobel (2019); Uhl (1980); Winters (2017); Woldeamanuel and Nguyen (2018)	1, 2, 3, 4, 7, 8, 11, 12, 13
Lack of transparency and missing verifiability	*Concerns about the lack of traceability of decisions by ADM, as decision-making takes place in the background ("black box") and is thus not comprehensible for individuals*	Brauneis and Goodman (2018); Strobel (2019); Westin et al. (2016); Yang et al. (2018)	1, 3, 8, 9, 13
Fading of individual influence	*Concerns about losing the ability to influence the decision-making process due to loss of personal bargaining power, as opposed to traditional decision-making*	-	1, 2, 3, 6, 7, 11

Omission of human decision factors	*Concerns about the lack of human elements (empathic capacity) in ADM's decision-making, i.e., soft aspects and special cases are no longer taken into account*	-	1, 2, 5, 8, 9, 10, 12, 13

The first category, *technology*, describes concerns about the technology used for ADM. *Breakdown of technology* is primarily seen as dangerous because "humans are highly dependent on technology" (Interviewee 10) and because technology could create "accidents involving humans" (Winters, 2017). The literature also shows that individuals are concerned about disruption to infrastructure (Winters, 2017) or potential system failure (Woldeamanuel & Nguyen, 2018). *Security incidents* refer to security concerns about system as a whole, and especially to the underlying data. Woldeamanuel and Nguyen (2018) indicate that the majority of individuals has security concerns, be they clear-cut security incidents or more general concerns about incidents associated with technology, e.g., the fear that someone may know when you are not home and then "burgle the house" (Interviewee 5, 13). Doubts that the system "will ever be mature enough to work 100%" (Interviewee 7) are summarized in the category *immaturity*.

The category *data* comprises concerns that individuals expressed about data used for ADM. *Privacy incidents* facilitated by "complete transparency of individuals" (Interviewee 1) are widely discussed in the literature (Alawadhi & Hussain, 2019; Coudert, 2010; Duarte, 2017; Newell & Marabelli, 2015; Strobel, 2019; Winters, 2017), and indeed in our interviews. The statements of Interviewee 12 ("the idea that one is completely predictable is daunting"), Interviewee 13 (who expressed concern about "having no control at all" over personal data), or Interviewee 11 (who said "data collected will be used for any other purpose") confirm the relevance of this issue. Concerns about manipulation of "the input that the algorithm receives" (Interviewee 9), e.g., via "false statements" (Interviewee 1), "paid advertisement that influences the algorithm" (Interviewee 1, 5), or that "small changes in the input data […] may lead to drastic changes in the output, making the result uninformative and easy to manipulate" (Yang et al., 2018) are summarized in *data manipulation*. *Insufficient or wrong data basis* includes, e.g., concerns about "weak points in the entered data, where you know they can be misinterpreted without further explanation" (Interviewee 3) or that data quality "depends on how well I maintain my personal data, e.g., how I answer the questions" (Interviewee 13), related to the thought that "an algorithm needs all data from my wife and me, and so it is not capable of booking a holiday for us, as it will never know how many and which compromises are possible and which are not" (Interviewee 10).

The category *decision* presents concerns that individuals have about the automated decision itself. Individuals are concerned about *poor decision quality*. They are convinced that "implementation will never be 100% correct" (Interviewee 1) and think that the algorithm cannot respond with sufficient sensitivity to highly individual needs. The topic of poor decision quality is also discussed in the literature as the fear individuals have, for example, about incorrect decisions (Strobel, 2019) or false recommendations. Furthermore, individuals are concerned about a *lack of transparency and missing verifiability* of decisions made by ADM, i.e., they cannot verify whether the decision really is the best one or "if it is only the third-best offer" (Interviewee 1), because they "don't know about the decision basis in the background" (Interviewee 1). Intransparency is another relevant topic in the literature, as individuals do not fully understand the opacity of a system (Westin et al., 2016). Meanwhile, *fading of individual influence* is discussed in the interviews with regard to "loss of bargaining space" (Interviewee 1) or a sense that there is no "possibility for a personal introduction, where my abilities might be recognized" (Interviewee 11) due to a lack of human involvement. O*mission of human decision factors* refers to "missing empathy" (Interviewee 9), "complete reduction to numbers" (Interviewee 5), and the thought that a "human can be better assessed by other humans than by algorithm" (Interviewee 12), especially in "exception cases" (Interviewee 12). Having illustrated the inherent concerns, Table 2.1-4 shows concerns about consequences of ADM.

Table 2.1-4 Individuals' concerns about consequences of ADM

Concerns	Description	Literature sources	Interviews
Physical			
Physical harms	*Concerns that use of ADM may result in physical harm, such as accidents involving individuals*	Brauneis and Goodman (2018)	6, 7, 13
Psychological			
Psychological harms	*Concerns that the feeling of being at the mercy of ADM systems has negative consequences on individuals' mental health*	-	13
Social			
Discrimination	*Concerns that existing discrimination in human decision-making is being systematized through ADM, leading to structural biases and unfairness in decisions*	Albarghouthi and Vinitsky (2019); Binns et al. (2018); Brauneis and Goodman (2018); Dietrich and Weisswange (2019); Kullmann (2018); Persson and Kavathatzopoulos (2017); Strobel (2019); Veale and Edwards (2018); Woldeamanuel and Nguyen (2018); Yang et al. (2018)	1, 2, 3, 4, 6, 7, 8, 11, 13
Resource-related			
Negative financial impact	*Concerns about ADM making decisions that are financially unfavorable for individuals*	-	6, 8, 13
Environmental harms	*Concerns about negative impacts on environment through the spread of ADM*	Winters (2017); Woldeamanuel and Nguyen (2018)	-
Prosecution-related			
Obscure legal regulation of responsibility	*Concerns about missing or unclear legal accountability for the decisions taken by algorithms*	Binns et al. (2018); Persson and Kavathatzopoulos (2017); Woldeamanuel and Nguyen (2018)	2, 3
Career-related			
Job loss	*Concerns about becoming unemployed due to widespread use of ADM*	Winters (2017)	-

Freedom-related			
Monopolization of economy	*Concerns about monopolization on a limited number of platforms which gain disproportionate power from data, leading to a centralized and unbalanced market*	-	1, 8, 11
Skill loss	*Concerns about individuals losing abilities or skills because they are no longer used to performing certain tasks*	Winters (2017)	2, 7, 8, 10, 12
Obscure explicitation of value system	*Concerns about a lack of morality in ADM or a mismatch between the moral values of the system and personal values*	-	1, 2, 4, 8, 12, 13
Negative effects on human well-being			
External determination	*Concerns that individuals give up more control over their lives to ADM systems (and organizations operating those systems)*	Newell and Marabelli (2015); Woldeamanuel and Nguyen (2018)	3, 4, 6, 8, 9, 11, 12
Lack of enjoyment	*Concerns that ADM decreases sensual and joyful moments, as the decision-making process itself is an enjoyable part of life that is no longer experienced by humans*	-	2, 6, 8, 9, 10, 13
Lack of individuality	*Concerns that ADM is not capable of reaching a level of individuality close to that of highly individual human decision-making*	-	1, 2, 8, 9, 12, 13
Lack of spontaneity	*Concerns that rigid patterns of ADM curtail the human value of spontaneity in daily life*	-	1, 4, 7, 13

Physical harms refer, for the most part, to accidents caused by ADM, e.g., via self-driving cars and other health hazards due to the increasing use of ADM technologies. In contrast, *psychological harms* denote “emotional damage” (Interviewee 13) through ADM. In the literature, Brauneis and Goodman (2018) also mention the concern that data can be used to hurt individuals.

Discrimination is among the most frequently discussed topics in the literature on ADM. Perhaps the most common form this takes is gender discrimination against individuals or protected groups (Kullmann, 2018; Persson & Kavathatzopoulos, 2017; Yang et al., 2018).

Our interviews confirm this, as many interviewees fear biased decisions due to the “discrimination between men and women” (Interviewee 8) and “exclusion of people who cannot afford or use technologies that get more and more sophisticated and therefore expensive” (Interviewee 11). Often, discriminatory decisions made by automated systems result from biased training data sets (Interviewee 1).

Furthermore, individuals are concerned about ADM having a *negative financial impact*, primarily caused by *data manipulation*, e.g., when an algorithm orders a product at “a disadvantageous price” due to a paid advertisement (Interviewee 8) or a faulty product that will not be used (Interviewee 6). The category *environmental harms* comprises aspects such as increasing air pollution or greenhouse gas emission (Winters, 2017; Woldeamanuel & Nguyen, 2018).

The following concern *obscure legal regulation of responsibility* is prosecution-related. Individuals fear that it is unclear “who bears responsibility if something happens” (Interviewee 3). One such concern relates to the use case of autonomous driving, as stated by Interviewee 2: “In case somebody dies, or gets injured or anything else, who is responsible?”

Individuals also have career-related concerns. Winters (2017) states that individuals fear losing their jobs (*job loss*) due to ADM.

The first concern in the category of freedom-related concerns is the *monopolization of economy*, meaning that “the market becomes more unbalanced” (Interviewee 1). *Skill loss* refers to the concern that with an increasing number of automated decisions and thus a diminishing proportion of human-made decisions, individuals lose human abilities, such as “empathy” (Interviewee 10) and decision-making skills (Interviewee 12). *Skill loss* also includes a concern about “humans becoming lazy or less industrious” and “losing certain abilities or skills” (Winters, 2017). In *obscure explicitation of value system*, individuals fear a lack of morality in ADM or a mismatch between the moral values of the system and personal values. For instance, this may result from distinct cultural backgrounds of an algorithm’s programmer and its users.

The subcategory of negative effects on human well-being comprises four concerns. Individuals prefer non-binding “recommender systems” (Interviewee 2, 8) in contrast to a completely automated decision in order to avoid *external determination*. The literature confirms these views, as concerns about dependence and loss of control have already been investigated (Newell & Marabelli, 2015; Woldeamanuel & Nguyen, 2018). *Lack of enjoyment* includes statements that ADM in private life is associated with having less fun. For example, decisions about food or traveling are perceived as "fun" (Interviewee 6, 9), and to some the decision-making process itself constitutes an "experience" (Interviewee 13), which is why some do not want to give up decision-making. Meanwhile, *lack of individuality* denotes concerns about the inability of ADM to reach a sufficiently high level of individuality in decision-making: "No matter how complex the algorithm, it will never offer a highly individual trip for me" (Interviewee 8). Another interviewee raised the question: "Where is the individuality?" (Interviewee 2). The *omission of human decision factors* is seen as the chief reason why ADM will not achieve sufficiently high individuality. Moreover, individuals are concerned about a *lack of spontaneity* through the use of ADM in their daily lives, as they feel that the algorithm cannot respond unprompted to changes, which is why there will no longer be any room for spontaneity (Interviewee 1). Incidentally, according to some individuals it is simply "nice if not everything is planned, but you just happen to stumble over something" (Interviewee 8).

2.1.5 Discussion

The interviewees confirmed concerns that were identified by the structured literature search. Only two concerns originating from the literature could not be confirmed by our qualitative content analysis (*job loss, environmental harms*). This might be due to the abstract nature of these two long-term consequences of ADM, which is to say that our interviewees may well have thought of those aspects as being too far in the future to be caused by single automated decisions. Yet these two aspects aside, the concerns discussed in the literature were supplemented by eleven further concerns that were first identified in our qualitative content analysis. To break down those numbers, four concerns were added to the literature on the left-hand side of the framework (immaturity, insufficient or wrong data basis, fading of individual influence, omission of human decision factors).

A closer look at the inherent concerns in Table 2.1-3 shows that only concerns in the category *decision* are unique to ADM. Conversely, *technology* and *data* concerns can also be transferred to other new technologies, such as the Internet of Things (IoT) or Blockchain. For example, *security* and *privacy incidents* have already been discussed in depth in the existing IoT literature (Leloglu, 2017; Naeini et al., 2005). Further concerns, such as *immaturity,* also pertain to other new technologies and are, therefore, not specific to ADM (Lepekhin et al., 2019). Concerns arising from these two categories – *technology* and *data* – can lead to concerns about consequences for individuals, organizations, or society, and these concerns can be held regardless of whether a specific automated decision is executed. For example, a *security incident* where personal data is stolen, which causes a *privacy incident*, might lead to discrimination in another context, one that is quite distinct from the original decision-making process during which the data was collected and therefore not governed nor indeed controlled by the initial decision.

As explained above, our framework contains eleven concerns that emerged solely from our interviews and have not been addressed in previous research. Within all categories, the interviews revealed new inherent concerns as well as concerns about consequences that lend themselves to further examination in future research (see Figure 2.1-1), which is strongly recommended in order to reduce individuals' skepticism about ADM and improve its acceptance among users. Some of the associated concerns worthy of further research are as follows: first, interviewees mentioned several aspects that mitigate their concerns about ADM, chief among them the fact that for many there is no perceived difference between ADM and a human decision-making process. For instance, interviewees often do not see a notable difference whether they provide their personal data to a human or to an algorithm. Furthermore, they tend to think that nowadays many organizational processes are already automated to a high degree, even though a human employee is involved. Another crucial aspect that would seem to attenuate many concerns is transparency. If individuals think they understand the decision-making process, which is to say that if they understand how and why the algorithm comes to its decision, many concerns are mitigated. A research area that focuses on this phenomenon is called explainable AI (XAI). XAI research analyses the black-box problem, i.e., that AI is becoming ever more complex. Hence, it becomes more difficult for the user to truly understand how the system works, and this diminishes the transparency of the user system (Bahdanau et al.). This, in turn, brings us to trust, the third mitigating aspect mentioned in our interviews. Individuals state that their concerns about a specific ADM system significantly decrease when they trust the system, for instance, if they have had good experiences with the same system in the past.

In addition to those attenuating aspects, interviewees mentioned potential positive aspects of ADM, as opposed to human-made decisions. These include time savings, less effort for individuals, less subjectivity and more fairness in decisions, variety and positive surprises through ADM, and lower error rate in decisions. Future research could be of interest to examine the relationship between those attenuating and positive aspects of ADM on the one hand and the afore-mentioned concerns on the other. It might be very helpful for the development of ADM systems to know which concerns could be addressed by which attenuating aspects and under which circumstance, or for instance in which use case a user will focus more on positive aspects and less on concerns.

To develop these findings into a coherent theory, we follow in the footsteps of Urquhart et al. (2010): “Theoretical integration means relating the theory to other theories in the same or similar field.” Since there is, at the time of writing this, no relevant theory to draw on with regard to ADM, we employ a related theory from the field of information privacy research. Specifically, we compare our framework with Karwatzki et al. (2017), who investigate adverse consequences of access to individuals’ information. What makes this comparison especially apt is that Karwatzki et al. (2017) examine individuals’ technology-related concerns and develop a comprehensive conceptualization and categorization in terms of physical, social, resource-related, psychological, prosecution-related, career-related, and freedom-related adverse consequences. In our own research, we transfer this categorization to the field of ADM and use it to structure individuals’ concerns about consequences, i.e., the right-hand side of our framework (see Table 2.1-4). What is more, we identify inherent concerns about technology, data or decisions, i.e., the left-hand side of our framework (see Table 2.1-3). Karwatzki et al. (2017) present very detailed manifestations in each category, i.e., concrete concerns (e.g., kidnapping and imprisonment, slander and bullying, stalking), and these also apply to ADM. For instance, the manifestation “financial loss (direct or indirect)” is very similar to our concern *negative financial impact* Karwatzki et al. (2017). Another example is the manifestation “being fired”. This relates to our concern *job loss* Karwatzki et al. (2017). However, Karwatzki et al. (2017) identified other manifestations, such as “time loss”, which do not apply to ADM as they are mentioned neither in the literature nor in our interviews.

Moreover, we expect our framework to provide several meaningful insights for individuals and organizations using ADM, and it is our express hope that our work in this area will lead to further research. ADM is a current topic of great interest and potential, but so far researchers have focused either on the possibilities of using and implementing ADM or on dealing with its technical consequences and ethical issues, while the concerns of individuals have only been considered selectively or disregarded entirely. None of the papers to date have focused on any reasons for reluctance from an individual’s point of view. Our primary theoretical contribution is, therefore, the understanding and structuring of concerns that prevent individuals from using ADM applications. Our framework can be used – either ex-ante or ex-post – to anticipate and evaluate problems associated with the introduction of ADM applications. We believe that our framework provides an interesting new perspective on this issue and will guide future research. Furthermore, it contributes to the extensive literature on the dark side of IS since it contains individuals' concerns and fears about using a specific technology, i.e., ADM.

Our results also offer practical benefits. A thorough consideration of concerns is essential as it can determine whether or not ADM applications are successfully disseminated. Our findings clearly show that some of the concerns are subjective feelings. Companies that implement or think about implementing ADM use cases should consider these concerns when developing ADM applications. They can use the framework to address these concerns, offer their prospective users targeted information, and strengthen trust in process outcomes based on automated decisions. Furthermore, our framework allows individuals to systematically gather information about ADM's potential risks for themselves and thus balance their concerns about ADM applications with facts. Many interviewees did not raise many concerns at the beginning of our interview but instead required concrete use cases to articulate their concerns.

Nevertheless, our research does not yet go far enough. Whereas the findings from the literature review are based on studies from different regions and countries, the interviews were all conducted in Germany. Expecting interesting cultural differences, the framework may be improved by extending the scope of the interviews to different countries (Bélanger & Crossler, 2011). Even though we included open questions regarding concerns about ADM at the beginning of each interview, future research may strive for more generalizability or test concerns for a specific use case. Moreover, future research may clarify the relationship between the concerns by collecting quantitative data and evaluating it, e.g., with factor analysis. Such future research may also contribute to the current discussion by developing appropriate countermeasures that address individuals' concerns about ADM.

2.1.6 Conclusion

The aim of this paper was to provide an overview of concerns about ADM and thus show the need for further research in this area. To date, the literature in the field has neglected the individual human side. Therefore, it has failed to account for the importance of individuals' concerns as limiting factors in the adoption of ADM. Based on a thorough structured literature search and semi-structured interviews, we identified the concerns already addressed in the literature as well as those it has so far neglected. In total, we identified 24 concerns associated with integrating automated decisions into a person's life. We structured these concerns in a framework divided into different categories: technology, data, decision for inherent concerns, and concerns adapted from the categories of Karwatzki et al. (2017). It is our belief that this framework will help in summarizing and communicating concerns about ADM with a view to increasing confidence in automated decisions. As a result, this framework shall also support the adoption of ADM applications and enable individuals to be better informed about potential risks.

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2.2 Individual concerns associated with the digital transformation in healthcare: Professionals' and patients' hindrances to adopt digital healthcare services

Abstract

Healthcare systems are facing enormous changes as digital technologies find their way to address current challenges. To foster acceptance of digital healthcare services in the future and support the digital transformation of healthcare, it is crucial to understand and overcome individuals' hindering factors in adopting digital technologies. This paper presents eleven hindering factors structured along four categories. These hindering factors are deduced from an in-depth interview study with 26 healthcare professionals and patients. Thus, we provide a sound set of individual hindering factors mapped on the well-established Unified Theory of Acceptance and Use of Technologies and discuss general implications for digital technology adoption in healthcare. Our paper is a first step towards addressing relevant hindering factors and can be used – either ex-ante or ex-post – to anticipate, explain, or evaluate problems with the adoption of digital healthcare services.

Keywords: Digital healthcare service, Technology adoption, Adoption behavior, Digitalization, UTAUT, e-Health

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2.2.1 Introduction

The healthcare sector has a long-standing reputation for being slow to adopt new technologies (Lucas et al., 2013), yet, finally, digital transformation has arrived (Pucihar, 2020; Vial, 2019). Driven by waves of digital innovations, digital technologies are now helping to realize the triple aim of improving the health of populations, enhancing experiences of care, and reducing the per capita cost of healthcare (Barello et al., 2015; Berwick et al., 2008; Devaraj & Kohli, 2000; Sharma et al., 2016). But change can also imply disruption and, in healthcare, we are currently facing enormous changes resulting from the increasing availability of digital technologies. Such technologies enable changes in healthcare value creation paths, as the structure of traditional healthcare services is extended to incorporate additional stakeholders, such as IT service providers. This can lead to positive and negative impacts, for example, privacy-related issues for users (Vial, 2019) which can hinder their acceptance and use of digital technologies in healthcare.

Regardless of its potential advantages and benefits, if a technology is not accepted – and, thus, not used – it creates no value. Therefore, the acceptance of technol Venkatesh et al. (2003)ogy has always been an essential aspect of information system research (Venkatesh et al., 2012), as has the acceptance of digital healthcare services (Hennemann et al., 2016, 2017). Currently, adoption levels of digital technologies (DTs) in healthcare remain relatively low. A 2018 study, for example, reported that 94% of patients in Germany are concerned about risks to privacy or misdiagnosis when DTs are used in patient consultations (PWC Health Research Institute, 2018). A recent study suggests that only one in ten healthcare professionals (for short: professionals) is highly accepting of digitalization (Hennemann et al., 2017). Subsequent research found similarly low acceptance rates among patients (Hennemann et al., 2018). One approach to analyzing the factors driving the acceptance of DTs is the well-established Unified Theory of Technology Acceptance (UTAUT), proposed by Venkatesh et al. (2003). The theory defines acceptance as the intention to use technology, directly determined by the four constructs *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions*.

However, individual concerns about undesirable outcomes resulting from digital transformation in healthcare may hinder the acceptance of a DT, as such concerns can negatively impact a user's expectations regarding the four constructs of UTAUT. To enable the targeted addressing of users' hindering factors in adopting DTs in healthcare, and to provide a holistic perspective on the topic, we see a need for an integrated, human-centered model that unifies factors influencing professionals' and patients' reluctance over DT adoption in healthcare. Therewith, we aim to improve the understanding of acceptance issues relating to digital healthcare services and enable factors underlying individuals' reluctance to be addressed. Directly investigating the individual, user-centric perspective will foster a broad understanding of acceptance among users – professionals and patients. In turn, this understanding will help to address factors contributing to this reluctance and, thus, to exploit the potential of digital transformation and digital healthcare service. Hence, we propose the following research question:

Which factors can hinder an individual's intention to use digital technologies in healthcare?

This research question leads to three research objectives: (1) We aim to uncover factors contributing to professionals' and patients' reluctance to adopt DTs in healthcare and, as raised by Vial (2019), concerns about resultant negative impacts in the healthcare value creation path. To provide a human-centered understanding of the factors hindering adoption, we empirically identify and analyze individual's perceptions of negative impacts resulting from the digital transformation in healthcare. (2) We aim to provide insights on technology adoption issues in healthcare by integrating the identified hindering factors in the UTAUT proposed by Venkatesh et al. (2003). (3) We aim to analyze how concerns differ between professionals and patients. To identify hindering factors, we conduct 26 interviews with the two main user-groups of DTs in healthcare – professionals and patients – which allow us insights into users' perceptions. We use open and axial coding to identify concerns from the interview data (Corbin & Strauss, 1990). The literature on technology acceptance and digital transformation in healthcare is reviewed and integrated during our research process. Drawing on our insights, we derive eleven hindering factors resulting from the changes in the healthcare value creation path. We then integrate these factors – which we assign to four main categories of *user*, *digital technologies*, *data*, and *resources* – into the UTAUT.

Our empirical results contribute to both research and practice. This study extends prior research on technology acceptance in healthcare by taking account of users' different perspectives on negative impacts resulting from digital transformation in healthcare, yet doing so from a DT- independent perspective. Our work contributes to practice by offering a differentiated understanding of factors that may inhibit technology acceptance. We make two key contributions of importance for service providers and chief executive officers in healthcare, in particular, those considering the digitalization of healthcare services. Firstly, our study recognizes that digital transformation in healthcare is a sensitive issue, and that there are manifold concerns among users that can hinder adoption. Secondly, we demonstrate that using our framework to map these concerns can help to address these hindering factors and foster acceptance.

This paper is organized as follows: Firstly, we provide a brief overview of digital transformation in healthcare services and its acceptance. Secondly, we outline our qualitative research method, its application, and our approach to answering our research question. Thirdly, we present the derived framework and illustrate the identified concerns and potential risks regarding digital healthcare services from a professional and patient perspective. Fourthly, we discuss the study, its implications and limitations, and present our conclusions.

2.2.2 Theoretical background

We aim to embed our study in the conceptual frame of digital transformation and technology adoption literature. Thus, there are two parts to our theoretical foundation: Firstly, we provide an overview of digital transformation in healthcare and the associated structural changes. Secondly, we review the current levels of acceptance and adoption of digital healthcare services and related approaches, like eHealth or health information technology.

2.2.2.1 Digital transformation of healthcare services

Digital transformation has emerged as an essential phenomenon in recent years, describing the profound changes related to the use of digital technologies (Majchrzak et al., 2016). Following Vial (2019), we understand the process of digital transformation to comprise eight main components: *digital technologies* create *disruption* triggering *strategic responses* to alter *value creation paths* while managing *structural changes* and *organizational barriers* that affect *positive* and *negative impacts*. This inductive framework is not domain-specific and, therefore, applicable to the transformations relating to digital healthcare services. And, as Lucas et al. (2013, p. 377), have pointed out: “IT-enabled transformation of health care is just beginning, and it cannot happen too fast.”

In healthcare, the *use of digital technologies* is also becoming apparent. Digital innovations propel digital transformation towards realizing the triple aim of improving the health of populations, enhancing experiences of care, and reducing the per capita cost of healthcare (Agarwal et al., 2010; Berwick et al., 2008; Gopal et al., 2019). The technologies that Vial (2019) refers to are also present in healthcare: social (e.g., Liu et al., 2017), mobile (e.g., Fedele et al., 2017), analytics (e.g., Kane, 2016, 2017), platforms (e.g., Reuver et al., 2018), and Internet of Things (e.g., Dang et al., 2019).

Consequently, digital technologies in healthcare enable *changes in the value creation paths* that affect the ways that healthcare services are deployed and newly created. In healthcare, these changes become apparent when looking at the differences between traditional and digital healthcare services. In traditional healthcare services, the primary interactions take place between professionals and their patients. Individuals interact with one another during the provision of medical services, exchanging relevant information and engaging in screening-, prevention-, diagnosis-, treatment-, and care-related service. Therefore, the main flow of information is between these two parties. With the adoption of digital healthcare services, traditional interaction changes as DTs become an integral part of information and communication during healthcare service delivery (Batalden et al., 2016; Srivastava & Shainesh, 2015). Another important stakeholder of digital healthcare services is the service provider, who is responsible for the knowledge, provision, and installation of DTs (Srivastava & Shainesh, 2015).

These changes in value creation paths generate both *positive and negative impacts* (Vial, 2019). Vial (2019) mainly refers to privacy-related issues that are also present in healthcare. As a consequence of this newly emerging triangular relationship, the amount of health-related data is increasing enormously (Senthilkumar et al., 2018). On the one hand, this offers new ways of providing digital healthcare services to patients (e.g., integrating other professionals or insurances). On the other hand, third parties have more opportunities to (illegally) gain access to the data generated (Abouelmehdi et al., 2017). Figure 2.2-1 illustrates our research focus based on a simplified version of Vial's (2019) framework.

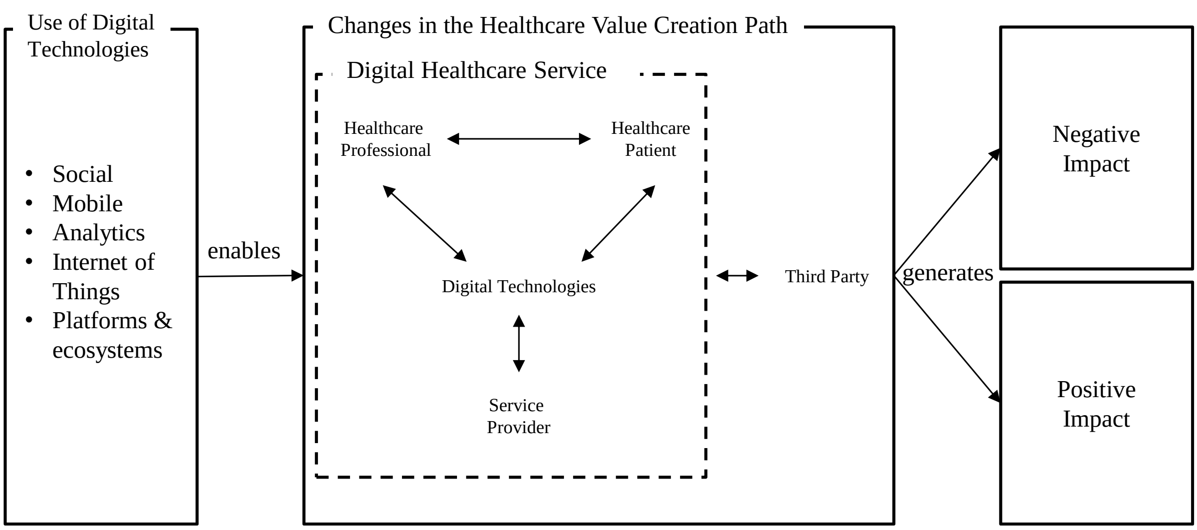

Figure 2.2-1 The process of digital transformation, proposed by Vial (2019), in digital healthcare services

Our study aims to address professionals' and patients' concerns about negative impacts resulting from structural changes to value creation paths (Vial, 2019). The use of digital technologies enables changes in the healthcare value creation path which have positive and negative impacts. Please note that Figure 2.2-1 summarizes basic flows of information – in specific services, some of these flows may be missing (e.g., the information flow between patient and DT in cases where the software is solely available to professionals). Further information flows might exist, such as for the service provider charging the patient for the service. However, this would not be part of the digital healthcare service itself and, thus, is excluded from Figure 2.2-1.

2.2.2.2 Technology adoption in healthcare

Technology adoption has received widespread attention. The understanding of individual acceptance and use of information technology is now a key research stream within the information system research community (Venkatesh et al., 2012). In general, adoption refers to the decision to use an innovation, for example, a service, product, process, or technology (Frambach & Schillewaert, 2002). The decision may be taken at an individual or an organizational level (Gopalakrishnan & Damanpour, 1997). In this research article, we investigate the decisions at the individual level; specifically, we examine the perspectives of professionals' and patients' as they represent the main users of DTs in healthcare and, therefore, their acceptance is decisive for technology adoption. Thus, we focus on individual users' perspectives on and concerns about DT's in healthcare.

Research on information systems proposes several theoretical approaches to technology adoption and healthcare uptake at an individual level. Well-established theoretical frameworks, such as the UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012), operationalize acceptance as the intention to use technology, which is directly determined by different constructs. The UTAUT proposed by Venkatesh et al. (2003) posits three direct determinants of the intention to use a DT, namely *performance expectancy, effort expectancy,* and *social influence*, and one direct determinant of usage behavior, namely, *facilitating conditions*. See Table 2.2-1 for the definition of these constructs.

Table 2.2-1 The four constructs of the Unified Theory of Acceptance proposed by Venkatesh et al. (2003)

Construct	Definition	Root Constructs
Performance Expectancy	The degree to which an individual believes that using the DT will improve performance	Perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectations
Effort Expectancy	The degree of ease associated with the use of the system	Perceived ease of use, complexity, and ease of use
Social Influence	The degree to which an individual perceives that important others believe he or she should use the new system	Subjective norms, social factors, image
Facilitating Conditions	The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system	Perceived behavioral control, facilitating conditions, compatibility

The UTAUT aims to explain an individual's decision-making process in accepting new DTs. The theory has been widely adopted, including in healthcare (Hoque et al., 2017; Kim et al., 2016; Kohnke et al., 2014; Wills et al., 2008), where results indicate a positive relationship between the constructs in the UTAUT and users' behavioral intentions (e.g., Wang et al., 2020). Further studies investigate drivers of and barriers to patients' (Ebert et al., 2015; Hennemann et al., 2016; Hoque et al., 2017) and professionals‘ (Ami-Narh & Williams, 2012; Hennemann et al., 2017; Li et al., 2013) acceptance of digital healthcare services, e-Health, or certain healthcare information technologies. These frameworks provide a useful lens to explain technology adoption in healthcare (Hennington & Janz, 2007). However, they must account for the specific technology in focus and its context (Jöhnk et al., 2021; Molla & Licker, 2005). Thus, they either investigate the adoption of a specific DT in healthcare or adopt the above-mentioned theories relating to a specific DT, context, or user group. However, a holistic view that unifies those factors discouraging users from adopting a DT is necessary to address technology adoption issues in a targeted manner.

Several studies, such as those by Hennington and Janz (2007) and Alaiad and Zhou (2017), use the UTAUT by Venkatesh et al. (2003) to illustrate factors hindering the adoption of technologies in healthcare settings. In some cases, these factors reflect specific properties of the DT, and in others, the context. We aim to build on these studies and apply a perspective independent from a specific DT to investigate hindering factors relating to changes in the healthcare value creation path. In doing so, we investigate factors hindering professionals' and patients' adoption of DTs for healthcare services. Previous studies on technology adoption in healthcare have reported low adoption rates among both professionals and patients. For example, Hennemann et al. (2017) surveyed German professionals and reported that nearly 50% displayed a low level of acceptance, 40% a moderate level, and only 12% a high level. Likewise, patients show similar low-to-moderate acceptance rates of DT adoption in healthcare (Hennemann et al., 2018). Thus, a shared understanding of DT adoption issues in healthcare will enable further targeted research and practice to address – and, thus, help to foster – technology adoption in healthcare in the longer term. Specific factors hindering technology use in the healthcare contexts have been examined in prior research. Privacy, in particular, is a major issue in healthcare due to the sensitive nature of health-related data (C. L. Anderson & Agarwal, 2011; Black et al., 2011; Dhagarra et al., 2020). In general, the collection and analysis of personal data are often perceived as negative due to the potential for adverse physical, social, resource-related, psychological, prosecution-related, career-relate, or freedom-related consequences for the individuals concerned (Karwatzki et al., 2017). Other factors affecting technology adoption in healthcare may include the effectiveness of DT in healthcare (Ariens et al., 2017; Ash et al., 2004; Blachetta et al., 2016) , the fear of technical failures (Fichman et al., 2011; Khan et al., 2012) , and the cost of DTs (Alaiad & Zhou, 2017).

In sum, recent research provides theoretical groundwork on technology adoption in healthcare, and on factors hindering in technology adoption by individuals, but does not identify relevant healthcare-specific, technology-independent hindrances that impede technology acceptance. Drawing on these previous studies, we seek to provide insights on factors hindering professionals' and patients' uptake, stemming from the fear of negative impacts resulting from changes in healthcare value creation paths. The resultant holistic view of these adoption issues and the ways in which hindering factors influence individuals' intentions to use DTs can, then, be linked with insights from general research on consumer behavior to provide a first step toward understanding the adoption of DTs in healthcare services. This will enable research and practice to foster technology adoption in healthcare in the long term.

2.2.3 Methods

We adopt a qualitative research method in this study to answer our exploratory research question on concerns regarding the digital transformation in healthcare (Bhattacherjee, 2012). Specifically, we use an interpretative research approach based on exploratory interviews.

2.2.3.1 Data collection

For this study, we conducted interviews with individual healthcare professionals, including doctors, nurses, and caregivers, and with individual patients from a range of demographic backgrounds. We selected these two groups (professionals and patients) to identify commonalities and differences (Orlikowski, 1993). We used purposive sampling to identify our interview partners. The selection of interviewees was based on criteria that the authors believe have an impact on concerns about the use of digital healthcare services, namely affinity for technology, health status, and profession. All of these factors were assessed by a self-assessment of the interviewees. This allowed us to holistically examine individuals' concerns about the use of DT in healthcare, to engage with the two main stakeholders of a digital healthcare service – the professionals and the patients – and to reflect on the key differences among and between these two user groups.

We continued to collect data until 'theoretical saturation' was reached (i.e., the incoming data from each group was no longer contributing relevant input). In total, we conducted 26 interviews with 12 professionals and 14 patients. The interviews took place either via video-conferencing or in-person. A detailed overview of the interviewees can be found in Appendix 2.2.A and Appendix 2.2.B.

Each interview lasted between 30 minutes and 50 minutes. The authors conducted the interviews equipped with detailed instructions and a semi-structured catalog of questions to ensure consistency. This approach provided initial guidance and the flexibility to accommodate the unique concerns of each individual. It also enabled the exploration of new and unexpected ideas (Karwatzki et al., 2017). We structured the interviews in three parts. Firstly, we asked the interviewee whether he or she had already heard of digital healthcare services, in general, to foster a shared understanding about the focus of the interview (Myers & Avison, 2002). Secondly, we asked some general questions on the topic of digital healthcare services. Thereby, we mainly focused on the interviewee's experiences of digitalization in healthcare in daily life and their concerns and hopes for the future. Thirdly, we presented different digital healthcare services (see Appendix 2.2.C for an overview of the presented services) and asking the participants for their thoughts on each of these services. The services have been selected so that they cover different medical areas and are in line with the latest developments in the field. In this part, we provided the interviewees with images and text to provide a clearer picture the different services. As language barriers during interviews can present significant challenges to researchers and may lead to misunderstanding (Squires, 2009), all interviews were conducted in the interviewees' native language (German).

2.2.3.2 Data analysis

All interviews were recorded and transcribed verbatim. The transcripts were then loaded into the software "f4Analyse," which facilitates the evaluation of qualitative interviews by allowing researchers to organize the different codes and categories identified. We performed an iterative analysis using open and axial coding, following Corbin and Strauss (1990). Firstly, we used open coding techniques to compare opinions and thoughts that our interviewees mentioned, and identified similarities and differences. We also identified preliminary categories with no prior categorization. In total, the first round resulted in over 800 codes and more than 30 categories. Secondly, we grouped the categories into themes during axial coding and investigated the relationships between these categories (Corbin & Strauss, 2008). We variously renamed and re-classified codes, merging those that were similar and excluding concerns that were not directly related to DTs in healthcare. This resulted in 12 concerns comprising 4 broad categories. The entire coding process was performed by three researchers in eight coding workshops, each lasting at least 60 minutes. Ongoing discussions and the comparison of codes and categories ensured a common understanding of the data. During both coding stages, we also reviewed literature on general technology acceptance and the digitalization of healthcare services.

As Glaser and Strauss (1967) observed, data collection and analysis are interrelated processes. The process does not merely involve reading an interview and conducting the analysis but consists of multiple steps. These include repeated consideration of the records, the identification of suitable passages, and comparisons with other interviews to identify codes. The aim was to develop a mutually exclusive, collectively exhaustive list of the interviewees' most pressing concerns about digital healthcare services. By doing so, we aimed to identify concerns common to both patients and professionals. If a concern was only held by members of one of these groups, it would show up in the results. However, it turned out that (on a level of abstraction that emerged in the codes), each concern was present for both patients and professionals.

Like research by Parks et al. (2017) and Karwatzki et al. (2017), our interpretive approach was guided by two criteria that ensure the (1) trustworthiness (Lincoln & Guba, 1985) and (2) adequacy of our research process and its empirical grounding (Corbin & Strauss, 2008). Firstly, trustworthiness ensures our research is credible, transferable, dependable, and conforms with necessary standards (cf. Appendix 2.2.D). Secondly, Appendix 2.2.E provides detailed information on the criteria used to evaluate the empirical grounding of our work. Thirdly, we follow Corbin and Strauss‘s (2008) criteria for evaluating interpretative research, which will help the reader to assess the adequacy of the research process (Parks et al., 2017). These criteria are evaluated and documented in Appendix 2.2.F.

2.2.4 Findings

Within the scope of our study, we identified eleven main factors hindering the digital transformation in healthcare, as perceived by professionals and patients. We assigned these factors, which were identified during the coding process, into four categories that specify fields of action that respond to incidences of risk and the occurrence of side effects related to DT in healthcare. Although these four categories are not entirely distinct, we believe they provide a good indication of the expected consequences of patients' and professionals' perspectives on changes in the healthcare value creation pathway which, ultimately, may lead to predicted negative impacts. Since the elements of the value creation path are interdependent, this also applies to the four categories and the hindering factors presented therein. Our results indicate that changes in the healthcare value creation path lead to negative impacts through the use of DTs and the increasing amount of personal, health-related data relating to users and resources. See Figure 2.2-2 for an overview of individuals' concerns regarding negative impacts resulting from the changes in the healthcare value creation path, adapted from Vial (2019).

2.2.4.1 Users

Users – namely, patients and professionals – represent the central agent in digital healthcare services. Hence, hindering factors in the category "user" comprise all concerns that directly affect users' personal integrity, self-esteem, dignity, and psychological health.

Discrimination describes the individual's concern that a user or user group will be treated differently, and notably worse, than others (L. M. Anderson et al., 2003; Peña Gangadharan & Niklas, 2019). An increased use of DTs in healthcare might lead to different medical services being made available to different groups of patients. This may relate to individual factors such as income, age, and affinity for technology, which can prevent or hinder access to and the use of DTs, resulting in the exclusion of certain patients or patient groups from the latest standard in healthcare. For example, the elderly might constitute such a risk group since their affinity for technology is often low: "*Elderly generations […] can [probably] not make use of digital healthcare services [as most of them] cannot even operate their mobile phones. Hence, the provision of digital healthcare services is an idea that is not beneficial for everyone*" (Professional 4). Patients expressed fears of being treated differently by others, including professionals or acquaintances, due to individual factors: *"Then, if I don't want to or can't use a service because it's too expensive or burdensome for me, am I a second-class patient?"* (Patient 12). The factor underlying this hinderance is the concern of negative impacts on the relationship between professionals and patients (Hennington & Janz, 2007). Patients are likely to feel excluded and may hold negative feelings towards their professionals.

Losing the autonomy to act, either objectively or in the user's perception, is a feeling of reduced individual freedom from external control or influence, resulting from the use of DT (Gimpel & Schmied, 2019). Firstly, professionals reported concerns about losing their objectivity, as DTs in healthcare offer service providers an opportunity to place targeted advertisements. The professionals spoke of their fear of being influenced or even manipulated to use a specific, promoted product rather than follow their own opinion on the best options for their patients. Professional 2 gave us a vivid example of a system for managing surgery that he uses in his daily work. This software "*[…] is sponsored by several pharma companies and on the sides [of the screen] the relevant advertisement is displayed. Hence, when [the software] notices, with the help of the information from the patient file, that the patient has diabetes mellitus type II, it displays a fitting advertisement. Alternatively, for a patient with problems of the thyroid glands, when it is was noted in the patient file as a diagnosis, suddenly an advertisement for L-Thyroxin […] appears on the right-hand side*". Similar remarks are also made by patients, who consider that *"companies are better at personalized advertising and try to influence [patients]"* (Patient 6). Through this influence, a certain amount of autonomy is lost, since "*there are enough people who say they are persuaded to purchase by personalized advertising"* (Patient 1). Another issue concerns the ease of access to, and richness of, patients' information. The overload of information can make it hard for professionals to objectively and thoroughly process all the information necessary to make a decision. For example, Professional 1 claimed that "*when a reviewer is writing a report and gets access to all patient data beforehand, is he then still truly objective?*". Overall, patients and professionals expressed concerns about a general loss of autonomy. This concern stemmed from a growing sense that they were no longer the only agents holding power in decisions about their patient's treatment, or from questions about their ability to make decisions without being manipulated. Underlying this hindering factor is a concern that decisions are not being made based on what practitioners feel is best for the patient but, instead, on what providers, health insurers, or the like dictate. This may negatively impact the performance and quality of digital healthcare services and may, thus, impede DT adoption in healthcare (Venkatesh et al., 2003). It may also negatively influence the professional-patient relationship as patients may lose trust in the professional's decisions.

Data fixation describes users' fear of being heavily dependent on their digital healthcare applications and the resulting data. DTs make it possible to capture a massive amount of health-related data. This risks reducing professional and patient perceptions of a patient actual health status to what is recorded and communicated in the form of data via DTs (Gimpel & Schmied, 2019). Patients may be overly concerned with their health status, for example, Professional 6 stated that the use of DTs *"can lead to a lot of focus on one's day-to-day well-being, which usually leads to the development of a very introspective personality that no longer becomes free and independent of the disease."* Likewise, professionals may be overloaded by their patients' data, or focus too much on previous patient's data. Professional 12 argued: "*Of course, it is good to learn as much as possible about the health background of my patient. But if a device gives me all this information, unfiltered, I will certainly be overloaded by all the information. I would rush through all the data and probably forget the most important thing: the patient and the conversation with the patient."* Patients, in particular, are concerned that "the professional is passing the responsibility, and follows the system's decision/suggestion*"* (Patient 1). Behind hindering factor is the professionals' and patients' concern of being too fixated on the data and missing important details on the patient available only at the interpersonal level. Additionally, it comprises patients' concerns about "*rely[ing] too much on digital healthcare applications*" (Patient 8), which, in the worst case, might lead to "*not noticing if the system does not work correctly and delivers wrong measured values because you have lost your sensitivity*" (Patient 8). Ultimately, some patients worried the result would be *"that one loses one's own body awareness or perception if one only relies on [digital healthcare systems]"* (Patient 7), or that one "*interprets too much into the data and the analysis"* (Patient 1) without critical assessment. Both aspects might negatively impact the performance and quality of a digital healthcare service, for example, when patients lose their sensitivity, which may impede DT usage.

Data responsibility describes users' concerns about obtaining the data necessary for service provision. This relates to professionals' and patients' concerns about whether data from DTs and patients can be collected accurately and reliably. Patients are concerned that, for example, data reflects *“symptoms […] described inaccurately [by patients], resulting in an inappropriate diagnosis”* (Patient 9). Other patients hold a similar perspective, emphasizing the aspect of the increased physical distance between patient and professional: *“I am worried that the doctor will receive too little or unreliable information if he does not see me in person”* (Patient 4). Likewise, professionals may question whether “data is still reliable” as it is “highly subjective and collected by [medically] unskilled users” (Professional 11). Underlying this hindering factor is the user’s responsibility for qualitative data and the fear of trusting inferior data, which may lead to a decrease in the quality of the healthcare service.

2.2.4.2 Digital Technologies

The newly introduced central agent in a digital healthcare service is the digital technology itself. However, users report concerns that emerge during or in response to DT usage. Hence, hindering factors in the category “use of digital technologies” comprise two aspects of DT use: a failing DT or a user that fails to use a DT correctly. These hindering factors also reflect current research on technostress (Ayyagari et al., 2011; Ragu-Nathan et al., 2008).

Unreliability of DTs describes all concerns accompanying the increased effort to offset technical problems such as crashes, hang-ups, or bugs (Ayyagari et al., 2011). The risk of technical problems bothers professionals as “*there is always the risk that the computer crashes or that there are other technical problems [and] that is a […] big problem […]. That is very dangerous*” (Professional 2). In addition to problems that can arise during the use of DTs, patients are also generally concerned about whether DTs function reliably or whether they have been *“poorly developed [...] and treatment errors occur as a result”* (Patient 6). This led to reluctance among patients to rely on such digital healthcare services *“as the only source of information, because a lot can go wrong”* (Patient 14). Firstly, this hindering factor stems from a concern that healthcare services may not be available due to a failing DT that cannot easily be repaired. Thus, the unreliability of DT can have negative impacts on performance. Secondly, the factor reflects users’ concerns about the effort needed to fix a failing DT during the service. Thirdly, it refers to an overall concern about whether the DT has been developed in such a way that it can reliably deliver value for the user (e.g., assessing correct data, determining appropriate treatments).

The **complexity of DTs** comprises all concerns about errors that occur due to the uninformed, or inexperienced application of DTs in healthcare services, and relates to concerns about the complexity of DT. Users may feel that their DT skills are inadequate (Ayyagari et al., 2011;

Ragu-Nathan et al., 2008). For example, patients express concern that they are *"unsure whether professionals are genuinely competent"* (Patient 14) or whether *"professionals are flooded with daily data [...] and are then [...] overwhelmed"* (Patient 8). But patients are also skeptical about their own abilities, and whether they are "*even able to deal with the complexity"* (Patient 1). In short, both patients and professionals may be afraid that they are not experienced enough to handle digital healthcare services due to the complexity of DTs. Yet, rather than admitting a lack of experience, some users may pretend to be "*experienced in using a technology, however, they are not. This can lead to huge problems due to incorrect application"* (Professional 7). Like above-mentioned concerns about unreliable DTs, the complexity of DTs may lead to performance-based and effort-based impacts when individuals use a DT in the wrong way or not as intended by the DT provider. This, in turn, may inhibit DT adoption in healthcare.

2.2.4.3 Data

The use of DTs means increases in the amount of medical information elicited and personal data collected. Hence, hindering factors in the category "data" comprise concerns stemming from the amount and variety of collected data and the integration of new stakeholders. Users fear that these stakeholders may (illegally) gain access to data which they may use for their own purposes, including to manipulate, invade privacy, or exercise power.

Invasion of privacy refers to concerns about data privacy – in particular, illegal accessing and use of personal, health-related data by third parties (C. L. Anderson & Agarwal, 2011; Black et al., 2011; Dhagarra et al., 2020). The increasing flow of information in digital healthcare services enables third parties, such as the service provider of the DT, to come into possession of patient data, leading to an increased risk of data leakage and, hence, abuse leading to privacy infringements. Individuals expressed concerns about the amount of sensitive, personal health-related data that may be misused or disclosed. Patient 3 explained: *"Collected data is not analyzed independently but is combined with other data from you. Thereby, much additional information can be generated."*. Patient 2 went further: *"Health-related data reflects much about you: how you live and what your daily routine looks like, for instance. You can deduce much information about people when looking at that kind of data. I don't want anybody to know about my health and my daily routine."*. Professionals also expressed an awareness of the sensitivity of patients' data: "*The moment a global computing or internet concern develops […] a digital healthcare application; the question arises: Where are the loopholes? I am sure they are there. Even if it appears to be anonymous, I would never* *advise my patients to implant [such] a device […] in their body as the company will get the power over the patient's data"* (Professional 2). Underlying this hindering factor are concerns about adverse exchange, social exclusion due to health-related data made publicly available, and the loss of one's privacy. All may lead to negative social consequences for the patient.

Data manipulation refers to concerns about third parties gaining illegal access to stored data and using it to maliciously manipulate the data's owner or the data itself (Agrawal & Alharbe, 2019). Medical instructions, decision-making support systems, or dosages can be manipulated or changed by third-party data-hacking, which can have disastrous consequences on the patient's health. Particularly in future, as the amount of personal information captured in electronic databases continues to grow at exponential rates, data security is likely to become even more critical (Angst & Agarwal, 2009). Patients raised concerns that the use of DTs in healthcare means that "*[data] manipulation becomes easier"* (Patient 2). Such concerns become even more significant when patients "[…] *imagine what would happen if a system or device gets hacked*" (Patient 1). Behind this hindering factor lies a concern about significant, performance-based consequences for a patient's health and life.

Super-powerful health insurance describes a concern about the increasing power of health insurance (Gimpel & Schmied, 2019). Health insurance companies have more access to individual patients' health data and other personal information, which they can use to their own advantage. Many of the interviewed professionals raised the concern that patients could be excluded from insurances or have problems being accepted by new healthcare insurance schemes if insurers gain access to particular health-related information. Likewise, when it comes to the treatment of their patients, professionals fear the increasing influence of insurance companies who may, for example, interfere with a patient's treatment financing. As one professional asked: "*Does the doctor have to justify himself to the health insurer to get the financing for his patient's care"*? (Professional 1). Likewise, popular programs, such as those that share wearable data in return for a discount on the insurance premium, let patients think about what would happen if they, for example, exercise less: In this case, "*[Would they] have to pay a higher health insurance premium than others? Health insurers might interpret this data to [a patients'] disadvantage*" (Patient 1). Although insurance companies assure patients that they do not have to fear adverse effects from sharing their data, patients remain suspicious "*which other benefits can health insurers derive from that data*" (Patient 4) – particularly in the future when data analytics provides new opportunities to handle the massive amounts of emerging data. Underlying this hindering factor is a fear of being dependent on health insurers. Afterall, if health insurers become too powerful, it may negatively impact the performance of a healthcare service, e.g., if cost coverage is refused.

2.2.4.4 Resources

DT use requires specific resources, such as money, time, and know-how. Thus, hindering factors in the category “resources” comprise all concerns referring to users’ resources. In contrast to the other hindering factors, those in the category “resources” can directly impact a user’s DT use-behaviour (Hennington & Janz, 2007).

Financial effort refers to the consequences of investing money in DTs in healthcare (Hennington & Janz, 2007; Jöhnk et al., 2021). Professionals and patients must invest financial resources to if they wish to use DTs in healthcare services. The lifecycle of DTs is short, and constant advancements in the field mean constant investments are necessary to keep-up with the newest technologies. As Professional 10 explains: *“You always have to stay up-to-date and keep up with all the developments in the digital field. These can lead to high costs for practice operators, for example.”* Monetary constraints and low budgets can prevent professionals and patients from adopting and using a DT in healthcare services. Such constraints can lead to difficult choices, particularly as some patients argue that, from their point of view, *“it is unclear whether it is worth the financial effort at all and whether the service will be better than before”* (Patient 1). Thus, the financial effort may be classified as a facilitating condition that can directly hinder DT use-behavior (Hennington & Janz, 2007).

Time effort refers to the time required to familiarize oneself with and learn to use a particular DT, and to handle malfunctioning DTs (Hennington & Janz, 2007). However, time is a scarce commodity, especially for professionals in healthcare contexts. As a consequence, some professionals pretend to be “*against the introduction [of DTs] because it takes so much time to set up and learn everything. I prefer to spend this time taking proper care of my patients”* (Professional 7). Similar thoughts were also expressed by patients, who found it *“difficult to imagine how the physician is supposed to devote time to the introduction and then deal with [the DT] in terms of their time”* (Patient 1), and questioned *“whether enough time is invested by [patients and professionals] to deal with the [DTs] in a meaningful way”* (Patient 4). Like financial constraints, time constraints may be classified as a facilitating condition that can directly hinder DT use-behavior (Hennington & Janz, 2007). Even if professionals and patients are willing to adopt a DT, they cannot do so if they do not have the time.

2.2.5 Discussion and implications

Our study builds on earlier research on digital transformation by Vial (2019) that observes changes in the value creation path. Based on 26 interviews with key users of a digital healthcare service – namely, professionals and patients –we explored hindering factors that impede the adoption of DTs in healthcare. Concerns about negative impacts on patients/professionals arise in response to changes in the healthcare value creation path. In total, we identified eleven hindering factors which we assigned to the four categories *users* (discrimination, losing autonomy to act, data fixation, data responsibility), *data* (invasion of privacy, data manipulation, super-powerful health insurers), *digital technologies* (unreliability of digital technologies, complexity of digital technologies), and *resources* (time effort, financial effort). These hindering factors stem from the changes in healthcare value creation path and lead to concerning negative impacts. Figure 2.2-2 depicts professionals' and patients' concerns associated with the digital transformation in healthcare.

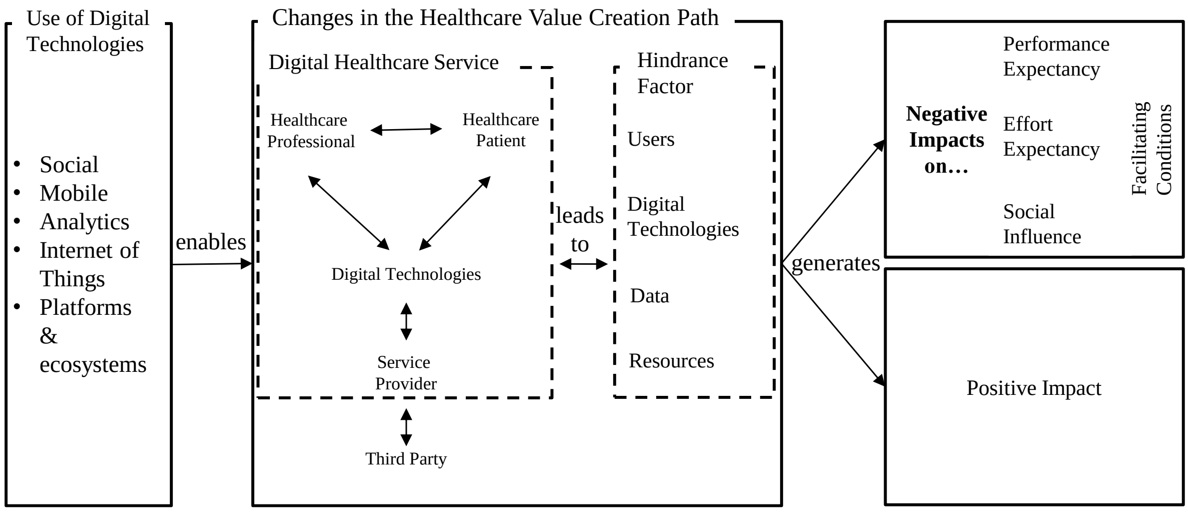

Figure 2.2-2 Model of professionals' and patients' concerns associated with the digital transformation in healthcare

Considering the nature of the healthcare sector, we highlight two important perspectives on adopting DTs in this specific field. Firstly, our results yield a holistic, unified understanding of factors specifically hindering DT use in healthcare that emerge as a result of including DTs in the healthcare value creation path. Some of these factors are not new to research on healthcare services and have been discussed in prior literature in the wider context of ongoing digitalization in healthcare (Esmaeilzadeh, 2019; Khilnani et al., 2020). These include, for example, the unreliability and complexity of digital technologies in terms of their implications on technostress (Ayyagari et al., 2011; Ragu-Nathan et al., 2008), discrimination based on individual differences (L. M. Anderson et al., 2003), and concerns about privacy issues, data manipulation, and security breaches (Abouelmehdi et al., 2017; Appari & Johnson, 2009). Secondly, our study provides an opportunity to compare differences between the factors hindering DT use among the two main stakeholder groups in healthcare services (see Appendix 2.2.G for a detailed overview). One thing that becomes apparent when comparing professionals' and patients' concerns is the similarity between the way concerns are perceived. We did not observe substantial differences in the way professionals and patients mentioned specific concerns about the user, the data, the use of DTs, or resources. Each of the eleven hindering factors was mentioned at least once by both a patient and a professional. However, there are differences in the way the stakeholders are affected by the hindering factors. It is mainly patients who are concerned about data manipulation, data fixation, invasion of privacy, and discrimination. On the other hand, professionals are mainly concerned about losing the autonomy to act, e.g., losing objectivity or being manipulated for the benefit of a third party. Last, professionals and patients are both equally affected by super-powerful health insurers, the unreliability of DTs, the complexity of DTs, and financial and time effort, e.g., when training to use a new DT.

The results of our exploratory interview study have enabled us to identify eleven factors providing clear reasoning for the adoption problems of DTs in healthcare. Yet, beyond recognition of these specific hindering factors, DT adoption in healthcare entails an understanding of their implications for an individual's intention to use a DT. Thus, the fact that concerns about negative impacts resulting from the use of DTs can hinder the adoption of DTs in healthcare (Hennington & Janz, 2007) emphasizes the need to specifically consider DT adoption in healthcare. Based on our results, we suggest a future research model for the empirical validation of the relevant adoption factors. In the following, we will position the results of our exploratory interview study within the existing literature on technology adoption, as shown in Figure 2.2-3.

2.2.5.1 Conceptualizing individual factors relating to DT adoption in healthcare

To embed our findings in the existing literature and investigate the effects of concerns surrounding DT adoption, we build upon the UTAUT proposed by Venkatesh et al. (2003). We argue that the eleven hindering factors identified in our study impact the four main constructs *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating condition* from the UTAUT. On this basis, we suggest that factors hindering individuals impede the individual's behavioral intention to use a DT, and negatively influence use-behavior (Hennington & Janz, 2007; Venkatesh et al., 2003).

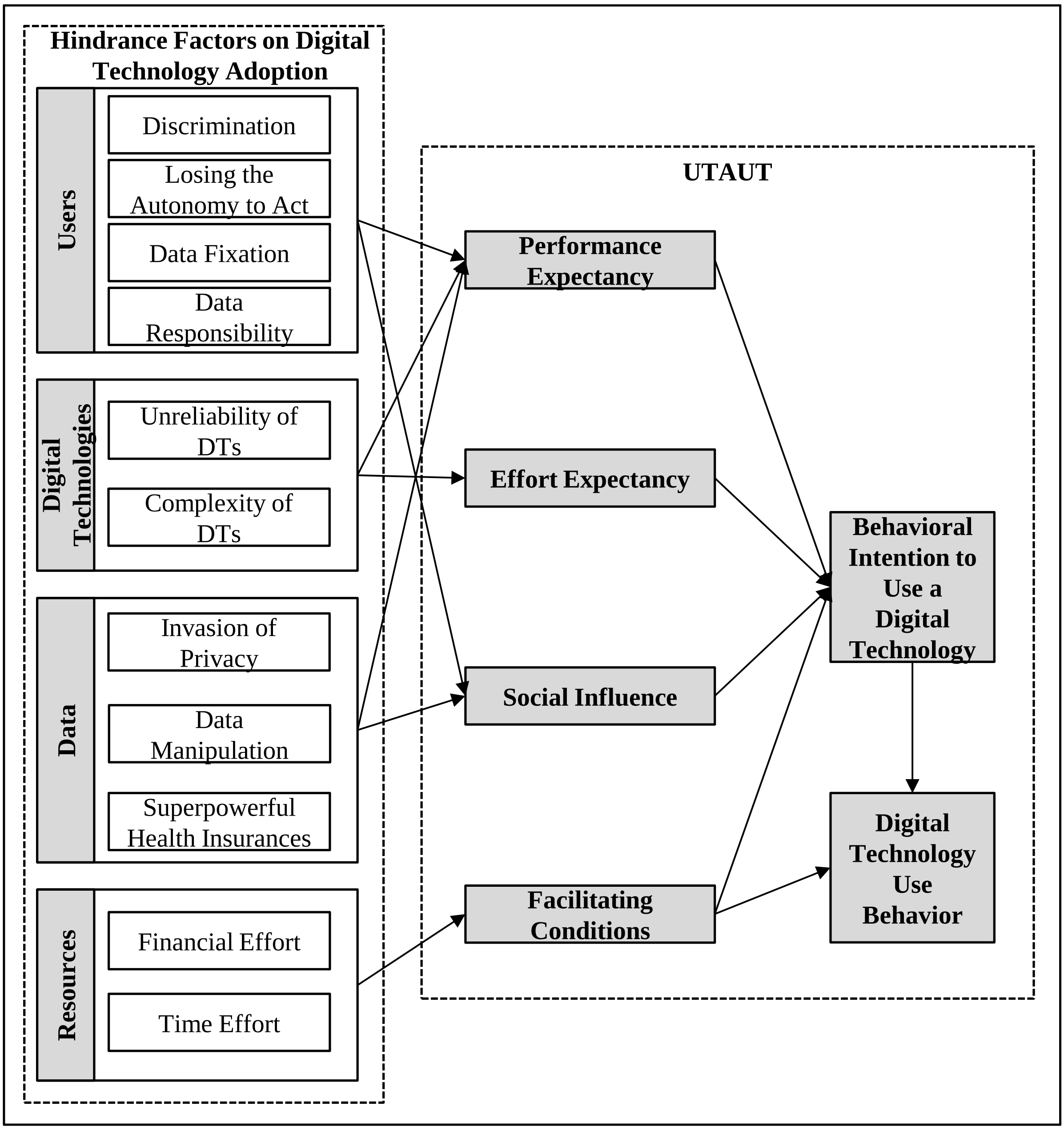

Figure 2.2-3 Factors affecting the adoption of DTs in healthcare

Firstly, our analysis revealed five hindering factors related to the performance expectancy of a digital healthcare service, which we suggest influence professionals' and patients' behavioral intention to use DTs in the context of healthcare services: losing the autonomy to act, data manipulation, super-powerful healthcare insurers, the unreliability of DTs, and the complexity of DTs. Performance expectancy is shaped by the individual's perception of the outcome of a digital healthcare service, and, thus, by improvements in the quality of the healthcare service (Hennington & Janz, 2007). However, professionals and patients fear that the adoption and use of DTs in healthcare may negatively impact the performance and outcome of a digital healthcare service, which may have implications on their behavioral intention to adopt DTs (Hennington & Janz, 2007; Venkatesh et al., 2003).

Secondly, our study highlights two hindering factors related to the effort expectancy associated with a digital healthcare service, namely, the unreliability and complexity of DTs. Effort expectancy is shaped by the individual's perceptions of the ease-of-use of a DT (Hennington & Janz, 2007). However, professionals and patients are aware of the efforts involved in adopting DTs. Thus, similar to performance expectancy, effort expectancy can hinder the individual's behavioral intention to adopt DTs in healthcare (Hennington & Janz, 2007; Venkatesh et al., 2003).

Thirdly, we highlight two hindering factors that impact social influence, namely, discrimination and invasion of privacy. Venkatesh et al. (2003) define social influence as the way in which individuals believe others will view them when using a DT, and conceptualize it using subjective norms, social factors, and image. Hennington and Janz (2007) highlight relationships with others, e.g., the relationship between physician and payer can impact social influence, affecting an individual's intention to use DTs.

Lastly, we suggest two factors relate to the facilitating condition: time effort and financial effort (Hennington & Janz, 2007). These factors are commonly mentioned as a hindrance to DT adoption and directly impact an individual's use-behavior (e.g., Bria, 2006, Leung et al., 2003, Mutlag et al., 2019, van Ginneken, 2002).

2.2.5.2 Implications for theory

Prior studies have revealed a low level of acceptance of DTs in healthcare among professionals and patients. To date, most studies on the acceptance of DTs in healthcare have focused on a certain DT or a specific context to examine technology adoption. However, a holistic understanding of DT adoption in healthcare is still missing. At the same time, however, technology acceptance is essential to exploit the potential that digitalization holds for healthcare services. By using an interpretive approach, our study was able to capture and gain insights into how professionals and patients feel about structural changes in the deployment of healthcare services and how these concerns lead to perceived risks. The use of interviews allows us to explore and understand professionals' and patients' concerns associated with the digital transformation in healthcare. Against this background, our research makes the following three contributions.

First of all, we identified eleven different hindering factors that prevent patients or professionals from using digital healthcare services. These hindering factors are the result of structural changes in healthcare services. By providing a unified overview of the perceived concerns and their associated risks, our research will help efforts to prioritize and address concerns held by both patients and practitioners. These eleven hindering factors can be grouped into four categories, namely user, digital technologies, data, and resources, which, together with the hindering factors they contain, lead patients and professionals to anticipate negative impacts.

Secondly, with the insights from our study, we now provide the additional empirical groundwork for theorizing technology adoption in healthcare and extending the digital transformation framework posed by Vial (2019). The four categories summarizing our hindering factors provide a good indication of the consequences both patients and professionals expect will result from changes in the healthcare value creation pathway and, ultimately, lead to negative impacts. This allows us to better understand how changes in the value creation path can lead to negative impacts and, thus, specifies the building block negative impacts in the framework posed by Vial (2019). Interestingly, the four categories are somewhat generic, meaning they can potentially be applied in other contexts related to digital services.

Thirdly, our study enriches insights from previous research by integrating individual concerns into the UTAUT. While several prior studies have applied technology models like the UTAUT to the healthcare context (e.g., Kohnke et al., 2014, Phichitchaisopa & Naenna, 2013, Wills et al., 2008), we contribute to the current literature on technology use in healthcare by providing an integrated and context-independent consideration of technology acceptance and users' concerns in healthcare. This allows the development of research models for the empirical validation of the relevant concerns accompanying the digital transformation in healthcare.

To summarize, this study addresses the need for a holistic understanding of professionals' and patients' concerns regarding digital healthcare services, and provides new theoretical insights into technology acceptance in healthcare. While we have focused on the so-far underdeveloped understanding of digital healthcare's dark side, future research may integrate the concerns and risks with standard technology acceptance models.

2.2.5.3 *Implications for practice*

In addition to the theoretical contributions, our research provides insights into challenges and opportunities for DT implementation in the healthcare sector. There are two main stakeholders: (1) service providers and chief executive officers in healthcare planning hoping to integrate DTs in their services and (2) the users, namely professionals and patients.

Firstly, DTs and digital services can offer benefits. However, there are examples of promising innovations that failed to diffuse because key actors were reluctant to use them (Angst & Agarwal, 2009). Thus, users' acceptance is crucial, and our study provides insights into major concerns. Our framework can be used – either *ex-ante* or *ex-post* – to explain, anticipate, and evaluate problems when switching to digital healthcare services. The early investigation of concerns among users is of great importance. It is an opportunity to, *ex-ante*, take concerns about risks into account when digital healthcare services are developed, and users can provide explicitly information about these concerns. If acceptance is low, an *ex-post* evaluation of the reasons can be carried out. In this case, our framework may provide insights into professionals' and patients' perceptions and can help to address their concerns.

Secondly, the framework can, likewise, improve the doctor-patient relationship by making doctors more aware of the concerns and risks that patients deal with and, hence, address these concerns more effectively. This also enables patients to obtain more targeted information about possible risks and to address or weigh up their concerns in a targeted manner regarding the respective digital healthcare service.

To summarize, digital transformation in healthcare is a sensitive issue as concerns among users can hinder adoption. These concerns should be considered *ex-ante* and *ex-post* when integrating DTs in healthcare services. Secondly, addressing these concerns may help to foster acceptance. Providers and users can profit from our framework by building upon the proposed understanding of technology acceptance.

2.2.5.4 *Limitations and suggestions for future research*

Our study has some limitations, which we believe offer opportunities for future research. Firstly, the purpose of our study was not to achieve statistical validation. We aimed to discover patterns for theory building and to gain a better understanding of the main issues in this context. It is reasonable to assume that our framework's insights will guide future research to develop a more formal theory (Orlikowski, 1993). Thus, we encourage future research to collect and test additional data to further clarify our findings and further incorporate the framework into theory. Likewise, more empirical and theoretical work is needed to more closely examine relationships among the seven concerns. In particular, complementary methods such as surveys or experiments could be used to extend our findings.

Secondly, this study was conducted in only one country and only with native speakers. Although we believe that our findings are partially transferable to other countries, healthcare systems worldwide vary widely. We cannot discount the possibility that users from other countries have different concerns than those in Germany, and researchers have already highlighted that there are differences in attitudes to information privacy across countries and cultures (Lowry et al., 2011; Posey et al., 2010). Future research should account for regional and cultural differences to test the generalizability of our results.

Lastly, we have limited our study to identifying professionals' and patients' concerns regarding digital healthcare services. We encourage future research to use our study as a starting point for going one step further towards addressing these concerns. A next step could be to integrate the concerns in a technology acceptance model analogous to those developed by Tan et al. (2012) and Lin and Kim (2016).

2.2.6 Conclusion

New DTs are providing more and more opportunities to tackle major problems in healthcare. They provide promising opportunities to realize the triple aim in healthcare – care, health, and cost – but only if they are accepted by users. However, users' willingness to adopt new DTs is often limited due to concerns specific to the context of healthcare, not least the sensitivity of health-related data. Building upon the framework of digital transformation proposed by Vial (2019), and interviews with professionals and patients, our research provides a thorough conceptualization of individuals' concerns about digital transformation in healthcare. Further, we discussed the integration of these concerns into the UTAUT. We believe that our study offers a starting point for future research on this topic and hope that it will help to fostering technology adoption in healthcare.

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Appendix

Appendix 2.2.A Overview of the professionals

ID	Gender	Age	Affinity for technology	Profession
Professional 1	F	50-60	average	Pharmaceutical technician, Alternative practitioner
Professional 2	M	20-30	high	Medical student
Professional 3	F	20-30	average	Nurse, Medical student
Professional 4	F	30-40	average	Physician (vascular surgeon)
Professional 5	F	20-30	average	Nurse
Professional 6	M	40-50	average	Physician (neurology)
Professional 7	F	50-60	average	Psychologist
Professional 8	F	30-40	Low	Physiotherapist
Professional 9	F	50-60	average	Psycholinguist
Professional 10	F	40-50	average	Midwife
Professional 11	F	30-40	average	Neuroscientist
Professional 12	F	30-40	average	Assistant Physician

Appendix 2.2.B Overview of the patients

ID	Gender	Age	Affinity for technology	Profession
Patient 1	F	20-30	high	Business and Information Systems Engineering
Patient 2	M	20-30	high	Computer Scientist
Patient 3	M	20-30	high	Research Assistant
Patient 4	M	60-70	average	Works Council
Patient 5	M	50-60	high	Software Developer
Patient 6	F	60-70	low	Retiree
Patient 7	M	20-30	high	Rescue Assistant
Patient 8	F	20-30	average	Children's Nurse
Patient 9	F	40-50	low	Seller
Patient 10	M	30-40	high	Computer Scientist
Patient 11	F	20-30	average	Law student
Patient 12	F	30-40	low	Administration in a hospital
Patient 13	F	40-50	high	Project Management
Patient 14	F	60-70	low	Retiree

Appendix 2.2.C Overview of the digital healthcare services presented in the interviews (translated version)

Digital Healthcare Service	Description
Online Consulting	A platform offers alternative counseling options for specific health issues. To do this, the patient must fill out a questionnaire after registering and then receive an initial medical assessment based on the symptoms reported and medical advice on how to proceed afterwards.
Self-Tracking	A new smartwatch from a worldwide leading technology company is also to be used in diagnostics and medical IT in the long term. Initially, it will include not only a fitness tracker but also a sleep tracker. This will not only store fitness data, but will also be able to collect and document health data in the long term. This will enable patients to log their activity (how many kilometers they have walked) and their body data (e.g. weight) and evaluate them using their cell phone and other special tracking programs. Furthermore, the results can be shared with friends via social networks.
Digital Twin	The provision of all health-related data in a central location will enable physicians in the future to create a virtual twin of each patient on whom they can try out their treatment. This enables systematic therapy and prevention by testing all possible treatments on virtual patients. In this way, undesirable side effects can be avoided. In cancer therapy, very good results have already been achieved with the modeling of tumors.
Telemedicine	A website offers to arrange virtual consultations with doctors from all over Germany. This means that specialists in particular can be consulted quickly, regardless of geographical distance.
Additional offers with the health insurance	A health insurance company is considering integrating the use of fitness wristbands into its bonus program. As part of a major promotion, this health insurance company is offering to provide financial support for the purchase costs of smartwatches and trackers. As soon as the insured person's number and some other information (e.g. weight, height, sports activities) are provided, up to 150 euros can be saved via a bonus program. In addition, the health insurance company advertises a bonus of €100 if sports activities can be documented with the apps or data from the fitness wristband.
Diagnostic Support	A worldwide leading technology company recently presented an intelligent contact lens for diabetics. This continuously measures blood glucose levels and warns of blood glucose fluctuations. The lens measures the glucose levels in the tear fluid every second and can thus assist in dosing the correct amount of insulin.

Appendix 2.2.D Evaluation of trustworthiness (based on Lincoln and Guba (1985), Parks et al. (2017) and Karwatzki et al. (2017))

Evaluation criteria	Goal	Appraisal
Credibility	Assessment of whether the results are believable	To ensure credibility, we carefully followed the established guidelines by Corbin & Strauss 1990 on how to conduct Grounded Theory Method. We gathered data from 26 interviews with professionals and patients who varied terms of age, affinity for technologies or profession, as described above. Despite their differences, in the end all interviewees raised similar concerns, indicating we had reached data saturation. In addition, our interview facilitators were well trained and conducted the interviews with great care. This provides us with further assurance that the insights gained in our research are reflective of reality.
Transferability	Assessment of whether the results can be applied to other contexts	To maximize transferability, we conducted interviews with a heterogeneous group of professionals and patients ensure our findings are context- and person-independent. However, due to multiple differences in healthcare systems around the world, we predominantly limit our findings to healthcare contexts in Europe.
Dependability	Assessment of whether the findings are consistent	In line with Parks et al. (2017) and Karwatzki et al. (2017), we have been engaged in constant scientific exchange with research assistants at the authors' departments, who provided critical feedback on our approach and the identified concepts.
Confirmability	Assessment of whether the results are confirmable	To ensure confirmability, we split our research process into three parts. While the first focuses on concerns regarding the use of digital healthcare services from a patient's perspective, the second focuses on concerns regarding the use of digital health services from a professional's perspective. Both phases were carried out until theoretical saturation was reached. The emerging results were merged into a holistic concept and, finally, in the third phase, evaluated by both patients and professionals and adjusted accordingly. Only once a round of interviews confirmed no further refinements were necessary was the concept finally confirmed

Appendix 2.2.E Empirically grounding of the study (based on Corbin and Strauss (2008), Parks et al. (2017) and Karwatzki et al. (2017))

Evaluation criteria	Goal	What to look for in this study?
Criterion 1: *Are concepts generated?*	Assess whether the concepts used in the research are grounded in the data	By analyzing the interview transcripts using open and axial, and constantly comparing and refining the concepts, the codes emerged. Therefore, all presented hindering factors are grounded in data. Exemplary quotations supporting our concepts are presented in sections focusing on respective hindering factors.
Criterion 2: *Are the concepts generated systematically related?*	Check whether there is are links between concepts	Our findings show how the hindering factors are related to one another. For example, we show that the professionals' and patients' hindering factors can be classified into eleven factors structured along four main categories. Furthermore, we map these hindering factors on the well-established UTAUT.
Criterion 3: *Are there many conceptual links and are the categories well developed? Do they have conceptual density?*	*Check whether the categories and subcategories are tightly linked*	We employed open and axial coding. Throughout these processes, the concepts related to subjective hindrances in using digital healthcare technologies that emerged were linked to one another, and several early concepts were merged into more general categories. Thus, we ensured the conceptual density of the categories by identifying and specifying the categories in detail.
Criterion 4: *Is much variation built into the theory?*	*Check for variations in the theoretical model and different conditions and consequences*	Our aim was to build an extensive framework indicating why individuals hesitate to use digital healthcare services and, thereby, to develop understanding of professionals' and patients' concerns. In doing so, we made sure that our framework is independent of the actual setting and, therefore, can be applied in Germany or countries with similar healthcare systems.
Criterion 5: *Are the broader conditions that affect the study built into its explanation?*	*Incorporate the micro and macro conditions*	Although our study aimed to identify subjective hindrances to the use of digital healthcare technologies, we expect that the importance of adverse hindering factors will vary across contexts (e.g., the healthcare system of the country, advances in digital healthcare services). Our framework offers a deeper understanding of how hindering factors impact the adoption of digital healthcare technologies, whereby perceptions of the significance of these hindering factors can differ.
Criterion 6: *Has process been taken into account?*	*Check if process has been considered*	We discuss conditions under which changes may occur in the Section 2.2.5.
Criterion 7: *Do the theoretical findings seem significant and, if so, to what extent?*	*Check for imagination and insights*	Our findings are context- and person- independent and have been carefully developed and grounded in our data. Thus, we think that our framework can help to address the adoption of digital healthcare services in further research supporting the relevance of our findings.
Criterion 8: *Does the theory stand the test of time and become part of the discussions and ideas exchanged amongst relevant social and professional groups?*	*Check whether theoretical framework is able to withstand future testing and research*	We are confident that our framework can be of use as a starting point for future research addressing the topic of technology adaption in healthcare. In particular, we would like to encourage researchers to conduct more studies in this research field and extend the scope of our framework. The emerging framework is comprehensive, and we believe that it will remain be stable over time. However, the rapid changes and developments in information technology may neccessitate extensions to our framework.

Appendix 2.2.F Research process evaluation criteria (based on Corbin and Strauss (2008), Parks et al. (2017) and Karwatzki et al. (2017))

Evaluation criteria	What to look for in this study?
Criterion 1: *How was the original sample selected? On what grounds?*	The collection of interview partners aims to construct a preferably heterogeneous group of professionals and patients to include as many different perspectives as possible before reaching theoretical saturation. The selection of interviewees was based on criteria that the authors believe have an impact on concerns about the use of digital healthcare services, namely affinity for technology, frequency of health services use, and educational background. The first interviewees were questioned from the immediate environment of the authors, and others were acquired in a snowball process.
Criterion 2*: What major categories emerged?*	In total, eleven hindering factors structured along four main catogores, which are associated with the use of digital healthcare services from the perspective of patients and professionals emerged: *users* (discrimination, losing the autonomy to act, data fixation, data responsibility), *data* (invasion of privacy, data manipulation, superpowerful health insurances), *digital technologies* (unreliability of digital technologies, complexity of digital technologies) and *resources* (time effort, financial effort)
Criterion 3: *What were some of the events, incidents or actions (indicators) that pointed to some of these categories?*	In each interview, the interviewer encouraged the participants to share as many digital-healthcare-related experiences as possible and discussed each of them in-depth. Besides, different use cases of digital healthcare services in concrete contexts were presented to the interviewees and discussed in detail to get a broader understanding of hindrances in using digital healthcare services. The hindering factors that arose were then coded and led to the categories and linkages reported in the Section 2.2.5.
Criterion 4: *On the basis of what categories did theoretical sampling proceed? That is, how did theoretical formulations guide some of the data collection? After the theoretical sampling was done, how representative did the categories prove to be?*	hindering factors in using digital healthcare services are the fundamental concepts within our study. Therefore, we applied an iterative process and gathered additional interview data from two different stakeholders within the digital healthcare service as long as new insights in terms of new consequences, new linkages to actors, or new mitigation mechanisms emerged. Across all interviews, we ensured having a diverse sample to cover all essential concepts. At the beginning of our research, some of the identified concepts were rather specific. However, most were later combined with other concepts and thereby merged into categories on a higher level of abstraction.
Criterion 5: *What were some of the hypotheses pertaining to conceptual relations (i.e., among categories), and on what grounds were they formulated and validated?*	Based on our data and an interpretation of them, we came up with hypotheses early on during data analysis. As an example of those hypotheses, this includes that, when it comes to accessing data from digital healthcare services, not only the malicious use of data by third parties (i.e., data abuse) but also well-intended use of data by third parties, for example, to display allegedly adequate behavior (i.e., discrimination) can be problematic and is a potential hindrance in using digital healthcare services.
Criterion 6: *Were there instances in which hypotheses did not explain what was happening in the data? How were these discrepancies accounted for? Were hypotheses modified?*	Throughout the coding process, categories and links between these categories have emerged. Some of these categories and their associated hypotheses have been preserved while others have been discarded. For example, in the beginning, we had the impression that interviewees were mainly concerned about the short- to medium-term effects of using digital healthcare services. We adapted this hypothesis and extended it accordingly to a long-term perspective when we discovered that, for example, this uncertainty about what will be possible in the future with already collected data from digital healthcare services, is a crucial factor.
Criterion 7: *How and why was the core category selected? Was*	Early on during the interviews, when we investigated participants' concerns regarding the usage of digital healthcare services, most of the

this collection sudden or gradual, and was it difficult or easy? On what grounds were the final analytic decisions made?	interviewees primarily talked about concrete harmful risks (e.g., loss of reputation, loss of money/time) that they were afraid of rather than abstract hindering factors. Nevertheless, we have chosen to focus on the concerns, as these are usually the underlying causes of harmful risks and allow specific conclusions to be drawn about hindrances in using digital healthcare services.

Appendix 2.2.G Overview about the occurrences of hindering factors in the interviews

ID	Users	Data	Digital Technologies	Resources
Professional 1	x	x		x
Professional 2	x	x	x	x
Professional 3		x	x	
Professional 4	x	x		
Professional 5		x		
Professional 6	x	x		
Professional 7		x	x	x
Professional 8		x		
Professional 9	x	x		x
Professional 10	x	x	x	x
Professional 11	x	x	x	
Professional 12	x	x	x	
Patient 1	x	x	x	x
Patient 2	x	x	x	
Patient 3		x		
Patient 4	x	x		x
Patient 5		x	x	
Patient 6			x	
Patient 7	x	x		
Patient 8	x	x	x	x
Patient 9	x	x		
Patient 10	x	x		x
Patient 11	x	x		x
Patient 12	x	x	x	
Patient 13		x	x	x
Patient 14	x	x	x	

3 Part B: Design approaches for information systems in organizations

3.1 Self-Services – Do not leave your customers alone with the technology

Abstract

New arising technologies change the modes of interaction between companies and their customers. So-called self-service technologies (SSTs) allow integrating customers as active participants into companies' business processes and thereby are expected to generate not only more efficient processes but also positive effects on customer satisfaction. As some customers do not consider their integration as an improvement and others are not able to use the SSTs, companies have to provide personal support offering direct response, assurance and social interaction. As for many companies the corresponding economic effects remain unclear, the aim of this paper is to develop a quantitative decision model that allows to decide on the integration of customers in business processes while considering of the necessary customer support on an economically well-grounded basis. To demonstrate the applicability of the model and its practical utility, we conduct a case study.

Keywords: Customer integration, Self-service technologies, Customer support

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3.1.1 Introduction

Customers nowadays increasingly value technology-facilitated interactions and transactions and hence the use and importance of SSTs is constantly growing. According to Gartner (2014), web self-services have grown from US $600 million in 2011 to US $1 billion in 2012 and annual transactions at retail self-checkout terminals are at US $250 billion and continue to grow (Barlyn & Carlton, 2007). There are several current trends fostering the use of self-services, like the increase in personal costs, the emerging digitalization, and the new self-understanding of the customers. The increase in personal costs in the developed countries makes an efficient use of personal resources necessary and forces employees to concentrate on value-generating activities (Mattheiss et al., 2011). This leads to customers taking over various responsibilities which formerly resided in the scope of the company. The emerging digitalization enables not only new technologies but also new communication channels which allow customers to act independently and produce value largely for themselves, on their own and without direct assistance from a service provider (Meuter et al., 2011). This by large meets with the new self-understanding of the customers (Burke, 2002). Considering the introduction of self-services, organizations face the challenge that not all business processes are suitable for the usage of SSTs and that it is uncertain how customers react to self-services.

Hence, over recent years, researchers have studied the various effects of self-service on the internal organization and the customers, e.g., the direct contribution to competitive advantage (Goffin & New, 2001) or reduced costs (Alpar, 1992). Based on this knowledge Negash et al. (2003) developed a quantitative economic decision model that determines where customer integration via SST should take place. Further approaches deal with the diverse methods of supporting the customers using self-services, e.g., web-based customer support systems (Negash et al., 2003) or support from front-line employees (Yen et al., 2004) were suggested. But no integrated view on economically well-founded decisions regarding the selection of those parts of a process which can and should be performed by the customers considering the corresponding support has been evolved. As customer support has become an important factor for companies' competitiveness with direct economic effects on the profit, it need to be considered in an economic model deciding on customers' integration (Negash et al., 2003). On the one hand customer support generates additional costs for services which influence the cash outflows. On the other hand support has positive effects on the perceived service quality and thereby animates customers to use the SSTs which leads to higher customer-related cash inflows (Anselmsson, 2001; Reinders et al., 2008). Thus, the aim of this paper is to develop a quantitative decision model which extends the model of Heidemann et al. (2011) by the effects of customer support and so allows for economically well-founded decisions on the integration of customers in business processes considering the corresponding customer support.

The remainder of this paper is structured as follows. In the next section, we provide an overview of the research background related to SSTs and support. On this basis, we develop a quantitative economic decision model. Then, we demonstrate the practical application of the model using the example of a global travel solutions provider. After a critical discussion of the results, we conclude with a brief summary and provide an outlook on future research.

3.1.2 Theoretical background

3.1.2.1 Customers' use of self-service technologies

Self-services are a constantly growing trend in Customer Relationship Management as they enable customers to transform from "passive audiences", who receive services and goods, to "active players", who take part in the business processes (Prahalad & Ramaswamy, 2000). Hence, self-services change customer-company interactions significantly (Meuter et al., 2011). As illustrated by a number of terms, which characterize the concept of self-service (Lengnick-Hall et al., 2000; Toffler, 1980), like "virtual customer integration" (Prandelli et al., 2006), "partial employee" (Mills & Morris, 1986) or "mass customization" (Hart, 1995; Piller, 2004), customers play an important role when integrating them into the companies' business processes. The development of new technologies fosters this trend as it enables customers to participate in the organization's work and hence, researchers have recognized the critical role of technology (Bitner et al., 2000; Meuter et al., 2011). These technological interfaces that allow customers to conduct a service independent of direct service employee involvement have been labelled self-service technologies (Meuter et al., 2011). These SSTs include for example e-commerce websites, Automated Teller Machines (ATMs), or kiosks (Meuter et al., 2011). Despite the growing presence of SSTs, it is still unfamiliar for many customers to engage as active participants in the organization's work (Lengnick-Hall, 1996), and thus customers may not be able or do not want to deal with SSTs. To determine how organizations can react adequately to the customers' needs and demands, it has to be examined if the customers are able and willing to use SSTs.

3.1.2.2 Customer acceptance and the role of personal support

The aim of self-services and SSTs is to provide numerous positive effects for organizations and customers (Payne, 2006). One of the main prerequisite for successful customer integration and participation is the customers' acceptance of SSTs. Therefore, a considerable part of the literature on self-services and SSTs examines determinants of customers' acceptance with, e.g., the help of the technology acceptance model (TAM) (Childers et al., 2001; Curran et al., 2016; Dabholkar & Bagozzi, 2002; Davis, 1989). According to TAM, the amount of technology acceptance is reflected in the strength of attitude or intention towards technology (Davis, 1989). The key drivers of customers' acceptance of SSTs are perceived usefulness, perceived ease of use, reliability, and fun (Weijters et al., 2016). Moreover, there are various determinants influencing the key drivers perceived ease of use and perceived usefulness (Rose & Fogarty, 2006): One of the most significant determinant is the personal contact between the customers and the employees as it supports those customers, who do not feel comfortable with technology, to embrace and use the new technologies (Meuter et al., 2005). Even with customers, who feel comfortable with technology, missing knowledge could diminish the use of SSTs, and hence organizations have to provide direct response, assurance, sense of control and social interaction (Rose & Fogarty, 2006). Regarding customer support there are two different ways to assist the customers: technical support (Negash et al., 2003) and personal support (Yen et al., 2004). Technical support includes, e.g., web-based customer support systems, where customers have the option to access support directly through the Internet and which are open to an unlimited number of customers needing support (Negash et al., 2003). Personal support in contrast to that can only be realized by personnel, e.g., by front-line employees (Yen et al., 2004) who directly assist the customers in every activity or sub-process in which they engage as active participants. Hence, we focus on personal support.

3.1.2.3 Effects of customer support

Various researchers have investigated the different positive and negative effects of offering personal customer support from an organizational perspective (e.g., Curran et al., 2016, Berry, 1999, Enkel et al., 2005, Hsieh & Yen, 2004). While there are several positive effects such as the expected increase of customer satisfaction or the potential reduction of costs, there are also negative effects like the dependence on customers' demands and personality. These positives and negative effects are summed up in Table 3.1-1.

While most of the presented studies deal with the positive and negative effects of offering customer support in a self-service environment from a qualitative point of view to the best of our knowledge, so far the existing quantitative economic models only treat the determination in which processes customers can and should be integrated but do not consider where and how much support should be offered. Hence, the following study extends the previous approaches to determine in which business processes customers should be integrated while considering the corresponding customer support.

Table 3.1-1 Positive and negative effects of customer support for companies

Effect	Description of effects	Approach
+	• increase success rate of new products • directly contribute to competitive advantage	Goffin and New (2001)
+	• reduce costs • increase productivity	Alpar (1992)
+	• improve competitiveness • increase market share	Kauffman and Lally (1994)
+	• rise customer satisfaction and customer loyalty	Meuter and Bitner (1998)
+	• increase speed of delivery • rise precision • higher customization	Berry (1999)
+	• avoid adversity • build long-term relationships	Negash et al. (2003)
-	• satisfy customer expectations regarding the level of service	Yen et al. (2004)
-	• dependence on customers' demands and personality	Enkel et al. (2005)

3.1.3 Decision model

For the potential integration of customers into business processes via SST, companies need to determine in which (sub-) processes customers can and should be integrated while considering the corresponding support. To assess these questions, we look at the economic effects of establishing SST and offering supporting activities and hence develop a quantitative economic decision model based on Heidemann et al. (2011) that addresses the necessary investments and the related process and customer effects.

3.1.3.1 Definitions

The economic decision model presented below is based on the following definitions:

D1: Business process and sub-process – A business process is defined as a collection of activities in a control flow that takes one or more kinds of input and creates an output that is of value to a customer (Dumas, 2013). A business process can be split into n sub-processes p_i ($i = 1, \dots, n$). These sub-processes are characterized as disjoint sub-sets of actions, which are connected in a control flow and form functional units. Sub-processes p_i can be performed either by the company ($p_i = 0$) or by customers via SSTs ($p_i = 1$).

If customers are integrated into business processes via SSTs, they take on a cohesive set of related tasks in the form of sub-processes (Heidemann et al., 2011). For each sub-process two possible ways exist to be performed that imply different integration variants for executing the business process (Heidemann et al., 2011).

D2: Integration variant – For each business process, there are 2^n possible integration variants $\vec{d}_j$ $(j = 1, \dots, 2^n)$. These variants can be expressed as a vector $\vec{d}_j = (p_1, \dots, p_n) \in \{0, 1\}^n$ and are characterized by which sub-processes p_i are executed by the company itself or by customers via SSTs.

As finally customers decide on the success of a service, the success of customer integration via SSTs depends not only on the adequate design of the process but also on the customers' attitude toward SSTs. Therefore, companies should comprise the preferences and behavior of their customers or rather of the target customer group in the decision process. According to their general attitude towards technologies customers can be separated into three groups: a group of technology-friendly customers (digital natives), who intuitively and quickly use or adopt new technologies, a group of elderly but open-minded adopters (digital migrants) and a group of elderly people with many digital deniers (Buhl et al., 2012). Depending on their affiliation to one of these groups, customers are more or less able and willing to perform a sub-process on their own and different extents of support have to be provided. Hence, for different target groups different integration variants can be optimal. To care for this fact we additionally extend the model of Heidemann et al. (2011) by considering the preferences of the target customer group.

D3: Target customer group – Since customers with a similar attitude towards SSTs also have similar requirements, e.g., regarding design and ease of use of SSTs and therefore a similar demand for support, this attitude can be used as a segmentation variable.

In the following, we focus on one specific target customer group. To decide whether and, if so, in which sub-processes p_i customers should be integrated via SSTs while considering the corresponding support, the following subsection presents an economic decision model that returns the optimal integration variant $\vec{d}_j^{\,*}$ for a specific target customer group.

3.1.3.2 Formulation of the decision model

All changes in cash flows that can be attributed to customer integration via SSTs need to be considered in an economically well-founded decision. The change of the net present value $\Delta NPV(\vec{d}_j)$ related to an integration variant $\vec{d}_j$ serves as decision criterion and can be identified according to Heidemann et al. (2011) by the following three elements: The present value of investment outflows for establishing customer integration via SSTs (investment effect) $I(\vec{d}_j)$; the changes in cash flows for process operations (process effect) $\Delta PE(\vec{d}_j)$, which represent the economic consequences of the changes in conditions of the process performance; and the indirect economic effects on customer behavior (customer effect) $\Delta CE(\vec{d}_j)$, which reflect the effects on the customer relationships caused by customer integration via SSTs (File et al., 1993). By this type of differential investment analysis, the change of the net present value $\Delta NPV(\vec{d}_j)$ can be denoted as follows:

$$\Delta NPV\left(\vec{d}_j\right) = -I\left(\vec{d}_j\right) + \Delta PE\left(\vec{d}_j\right) + \Delta CE\left(\vec{d}_j\right) \tag{1}$$

This calculation is based on the external circumstances (e.g., currently available technological configuration) at the time of the decision. As customers are not necessarily able to immediately – if ever – take over the new responsibilities that come along with the SSTs and to perform all tasks by themselves, companies need to support them. But supporting customers has direct economic effects on the cash outflows and the customer-related cash inflows and thereby affects all three components of the net present value (NPV). Thus we extend the elements identified by Heidemann et al. (2011) by considering customers' support when specifying the composition of the NPV.

Investment effect: Actions to set up SSTs are considered as investments. Generally, setting up SSTs requires investments for facilities as well as organizational and technical changes (e.g., infrastructure, hardware such as self-service terminals, or software functionalities). Concretely, the present value of investment outflows for establishing customer integration via SSTs $I\left(\vec{d}_j\right)$ includes overarching outflows for an integration variant $\vec{d}_j$, such as investments for project and business process management $V_j^{total} \in R_+$ and particular investments $\vec{V} = (V_1, V_2, \ldots, V_n)^T \in R_+^n$ for each sub-process p_i, that a customer can carry out, such as hardware or software. Furthermore, as customers need to get used to the new mode of interaction usually intensive initial support is required (e.g., initial explanation of the new tasks, providing training and advice). This go-live support causes additional one-time expenses for each sub-process p_i, which are represented by the vector $\vec{g} = (g_1, \ldots, g_n)^T \in R_+^n$. In sum, $I(\vec{d}_j)$ can be described as follows:

$$I\left(\vec{d}_j\right) = V_j^{total} + \vec{d}_j \cdot \vec{V} + \vec{d}_j \cdot \vec{g} \tag{2}$$

Process effect: Furthermore, independent of whether sub-processes are performed by the company or by customers, it is necessary to ensure that the process can be successfully completed. Depending on the integration variant, there are changes in cash flows for process operations for, e.g., materials, rent, personal payments, and maintenance for each sub-process $\overrightarrow{\Delta B} = (\overrightarrow{\Delta B}_1, \overrightarrow{\Delta B}_2, \ldots, \overrightarrow{\Delta B}_n) \in R^n$. Besides these payments, additional expenses for customer support occur for each sub-process where customer integration takes place. These expenses for customer support can be expressed by a company-specific cost rate $\vec{c} = (c_1, c_2, \ldots, c_n) \in R_+^n$ representing the present value of the wage of staff in relevant service and support functions. For each sub-process p_i, c_i corresponds to the costs if 100% support is required (do-it-all-for-them). How much support really needs to be provided depends on the customers' ability to use SSTs which in turn is determined by their knowledge regarding the specific sub-processes and their willingness to perform (Büttgen, 2007). Since SSTs foster learning and knowledge creation (Gray et al., 2013), customers' knowledge about a specific sub-process develops over the time (Unterbruner & Unterbruner, 2005). Furthermore, customers' knowledge is influenced by different factors such as the complexity, the frequency of the executions and the general awareness level of the sub-process (Bouncken, 2000; Thissen, 1997). These influencing factors are represented in the following by a sub-process specific growth factor $b_i \in (0,1)$. Precisely, customers' knowledge $k_{i,t}$ about a specific sub-process p_i at the beginning of the period$t \in (1,2, \ldots, T)$ corresponds to their knowledge about p_i at the end of the previous period t. Within a period t, $k_{i,t}$ develops according to the sub-process specific growth factor b_i. Thereby, the first units of knowledge can be acquired more quickly (Unterbruner & Unterbruner, 2005) as the basics about a specific sub-process are easier to learn than the further expert knowledge. We then assume a phase of declining growth until an upper bound k_i^{max} is converged. This sub-process specific upper bound k_i^{max} represents the maximum of knowledge about the sub-process p_i customers may have. Thereby, we exclude the special case that the customers already hold the maximum knowledge k_i^{max} about a sub-process before the first execution. Hence, customers' knowledge at a specific period can be described as follows:

$$\boldsymbol{k_{i,t}} = \boldsymbol{k_i^{max}} - \left(\boldsymbol{k_i^{max}} - \boldsymbol{k_{i,t-1}}\right) \cdot \boldsymbol{e^{-b_i}} \tag{3}$$

with $k_{i,t}$: customers' knowledge about sub-process p_i in period t with $k_{i,t} \in \left(k_{i,0}, k_i^{max}\right) \forall\, i = 1,..,n$

$k_{i,0}$: initial knowledge about sub-process p_i before the first execution with $k_{i,0} \in (0, k_i^{max})$

The total sub-process specific customers' knowledge K_i is determined as the average of these periodic values:

$$K_i = \left(\sum_{t=0}^{T} k_{i,t}\right) \cdot \frac{1}{T} \tag{4}$$

As mentioned above, the customers' willingness is a further important influencing factor of customer support. Different stimulations – represented by support – can be used to motivate customers to execute more active work than before (Gray et al., 2013). If customers do not want to perform, they will need more support (do-it-all-for-them) than if they like to do it but require help, e.g., because of a lack of knowledge (support-on-demand). This customers' willingness to use SSTs is affected by their attitude towards SSTs which in turn can be expressed by their technology affinity $a \in [0, 1]$ (Davis, 1989). Depending on the regarded target customer group, a can range from skepticism ($a = 0$) to excitement ($a = 1$) (Karrer et al., 2009). Customers who like to use SSTs, so-called "digital natives" ($a = 1$), just need support depending on their knowledge about the process. Customers with a low technology affinity, the "digital migrants" and "digital deniers" ($a < 1$), in contrast need more support as required on the basis of their knowledge to execute the process successfully. Thus, depending on the integration variant $\vec{d_j}$, the level of customer support $\vec{s_j}$ can be determined by the following formula:

$$\vec{s_j} = diag\left(\vec{d_j}\right) \cdot (\overrightarrow{1_n} - \vec{K} \cdot a) \tag{5}$$

with $\vec{K} = (K_1, K_2, \dots, K_n)^T \in R_+^n$,

$\overrightarrow{1_n} = (1,1,\dots,1)^T \in \{1\}^n$ as the unit vector,

$diag\left(\vec{d_j}\right) = \mathrm{I_n} \cdot \vec{d_j} = \begin{pmatrix} p_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & p_n \end{pmatrix}$ with I_n as the identity matrix, since customers only need to be supported within those sub-processes p_i, where customer integration takes place ($p_i = 1$).

Finally, customer support can be interpreted as the maximum of 100% support (do-it-all-for-them) minus the percentage customers are able to perform on their own depending not only on their knowledge but also on their willingness $(\overrightarrow{1_n} - \vec{K} * a)$. As each unit of support provided to a customer causes additional personnel expenses, support should be considered by the economic decision model for the optimal level of customer integration. Summarized, $\Delta PE(\vec{d_j})$ can be denoted as follows:

$$\Delta PE\left(\vec{d_j}\right) = \vec{d_j} \cdot \overrightarrow{\Delta B} - \vec{s_j} \cdot \vec{c} \tag{6}$$

Customer effect: Customers perceive a subjective total process experience (Meuter et al., 2005) that depends on which sub-processes are executed by the customers themselves and thus differs for each integration variant $\vec{d_j}$. More precisely, the conformity of SSTs to the key drivers of customer acceptance (such as perceived usefulness, perceived ease of use, reliability and fun (Weijters et al., 2016)), influences the customers' experience regarding the whole process. Personal support is thereby a significant determinant influencing the perceived ease of use and perceived usefulness. It not only provides direct response, assurance, sense of control and social interaction for customers who do not feel comfortable with the SST (Meuter et al., 2005) but also for customers who feel comfortable but are not able to use the SST alone because of missing knowledge and experience (Rose & Fogarty, 2006). Creating superior experience for the customers is of importance, as it results in higher customer satisfaction which in turn may lead to an increase in customer-specific sales and recommendation rates (Anderson, 1994) and hence generates higher expected customer cash flows. Contrary, if customers are dissatisfied or scared of to the SST and the provided support does not succeed in compensating the inconveniences on customers' side, negative customer experience could also decrease the expected cash flows. The resulting changes in customer-related cash flows are reflected in the corresponding change in customer equity which is defined as the sum of the discounted cash flows of all customer relationships (Rust et al., 2018) and represents the amount these customer relationships contribute to corporate value. Hence, customer support affects $\Delta CE\left(\vec{d_j}\right)$.

Considering customer support in the economic decision model to determine the optimal integration variant $\overrightarrow{d_j}^*$, which indicates in which sub-processes p_i customers of a certain target group should be integrated via self-service from an economic point of view, can be expressed on the basis of the above defined assumptions and terms as follows:

$$\Delta NPV(\vec{d}_j) = -(V_j^{total} + \vec{d}_j \cdot \vec{V} + \vec{d}_j \cdot \vec{g}) + \vec{d}_j \cdot \overrightarrow{\Delta B} - \vec{s}_j \cdot \vec{c} + \Delta CE(\vec{d}_j) \tag{7}$$

with

$$\vec{d}_j^{\,*} = arg \max_j NPV(\vec{d}_j) \tag{8}$$

maximizing the net present value of the whole business process.

As described in D2 a maximum of 2n integration variants $\vec{d}_j$ are possible for each business process. For the determination of the optimal integration variant $\vec{d}_j^{\,*}$, it is possible to use combinatorial methods or a full enumeration of all realizable integration variants $\vec{d}_j$. To simplify this approach it can be helpful to eliminate integration variants which are not feasible, as some sub-processes should not be handed over to the customers.

3.1.4 Case study

3.1.4.1 Case setting and unit of analysis

To test our model practically we conducted a case study with the fictional setting of a global travel solutions provider for business customers. The company develops customized travel management solutions along the entire travel booking value chain – from flight and hotel procurement to processing bookings and innovative payment solutions. The core process of the company is the booking of business travels. Figure 3.1-1 illustrates the sub-processes of this booking process.

Figure 3.1-1 Booking process

To date, customers are not integrated in the booking process but generally they could take over the responsibility for certain sub-processes of the whole booking process. Thereby some sub-processes such as providing personal data are straight forward but others such as the correct accounting data require expertise (either by the customers themselves or by employees). Hence the success of SSTs and the economic value of the customers' integration cannot directly be predicted but needs to be analyzed in detail. Basically, customer integration via SSTs is possible in p_1, p_2, p_3, p_4. The sub-process p_5 is the core service delivery of the regarded company and requires internal information and authorizations (e.g., special price conditions). Because of its strategic relevance, the company decides not to integrate any customer in sub-process p_5. Therefore, there are $2^4 = 16$ possible integration variants $\vec{d_j}$ to be investigated.

Genuine values for the theoretically developed model parameters were acquired via a case study and experienced estimation. First, a case study with 34 test users has been conducted in order to determine input parameters such as initial knowledge about sub-process p_i before the first process execution $k_{i,0}$, sub-process specific upper bound of the maximum of knowledge about the sub-process p_i customers may have k_i^{max}, sub-process specific growth factor b_i and technology affinity a. Thereby, the participants had to complete surveys with questions about their person, their technology affinity, and their experience. Additionally, they executed the whole process on their own (with the option to ask for personal support at any time). On the basis of the estimations of subject matter experts, the company specific cash-flow components were determined. For confidentiality reasons, the data were slightly modified, but without compromising the basic results.

3.1.4.2 Determining the model parameters

As presented in Section 3.1.3, the core parameters of the model are the present value of the investment outflows for establishing customer integration via SSTs $I(\vec{d_j})$ (investment effect), the changes in cash flows in process operations $\Delta PE(\vec{d_j})$ (process effect) as well as the indirect economic effects on customer behavior $\Delta CE(\vec{d_j})$ (customer effect). These parameters were operationalized and determined for each integration variant $\vec{d_j}$ as described in the following. For the calculations, we assume an imputed interest rate of 2% p. a. and a calculation period of five years.

Investment effect: As the interviews revealed, integrating customers in the sub-processes $p_1, \dots, p_4$ requires no self-service terminals, but new software functionalities for the search steps and the various data entries. The experts' estimation provided the following data: Designing new software or extending existing tools results in immediately effective expenses of € 300,000. Project management to establish customers' integration can be assumed (comparing to empirical values from previous projects) to be 200 in-house person-days (200 * € 500 = € 100,000). Additionally, expenses for training of employees have to be considered when at least one sub-process is performed by the customers. Regularly, seven employees perform the regarded process but taking replacements (e.g., due to vacations) into account ten employees should possess the knowledge required and hence have to be trained. For the necessary training of three days, one training day was calculated with an average in-house per diem of € 500. So, the estimated training costs amount to € 15,000. Furthermore, initial intensive customer support (go-live support, e.g., for initial explanation of what customers should do or where they can find information) causes one-time additional expenses for each sub-process. These are for the customer integration in, e.g., sub-process p_3 € 50,000.

Process effect: Regarding the process operations, self-services result on the one hand in savings due to the change of personnel payments and reduced printing costs. On the other hand, expenses for IT systems and customer support occur. In detail, according to the estimations, the savings in personnel costs result from a decrease in working hours per process execution and the present value of the hourly wage rates of the staff working in the corresponding sub-process. For the customer integration in, e.g., sub-process p_3 these potential savings are € 1,277,165. The savings of printing costs (forms of two pages for p_2, p_3 and p_4) are caused by the removal of the required forms as physical hard copies. Assuming 500,000 bookings of business travels a year and € 0.03 printing costs per page, the potential savings for, e.g., sub-process p_3 are € 30,000 p.a. (500,000 * 2 * € 0,03). The additional costs for IT occur because the regarded company needs further computing capacity and storage volume which result in expenses of € 24,000 p.a. Furthermore, expenses for customer support arise for each sub-process with customer integration. Customer support $\overrightarrow{s_j}$ is calculated according to the terms (3)-(5). The necessary model parameters (sub-process specific initial knowledge $k_{i,0}$, growth factor b_i, upper bound for the customers' knowledge k_i^{max} and technology affinity a) were derived from the customer surveys. From the captured data, the expenses for customer support for, e.g., sub-process p_3 amount to € 203,848.

Customer effect: As achieving customer satisfaction is one of the central business policy goals, the operationalization of the customer effect of customer integration uses customer satisfaction as a metric. Personal contact between the customers and the employees is a significant determinant influencing the perceived ease of use and perceived usefulness and can hence increase customer satisfaction. In the context of the case study, this was captured via customer surveys using differentiation based on a five-step Likert scale (1 = very satisfied; 5 = very dissatisfied). One result, for example, was that an integration in sub-processes p_1, p_2, p_3 improved customer satisfaction from 3.2 (status quo) to 2.9. In order to achieve a corresponding change in customer satisfaction in another way, experiential values indicated that it would be necessary to make alternative marketing investments of approximately € 180,000 p.a.

3.1.5 Results and discussion

On the basis of the identified parameters, the optimal integration variant $\vec{d_j}^*$ can be determined corresponding to terms (7) and (8). The optimal integration variant maximizes the NPV of all cash flow changes attributable to customer integration via SSTs in the analysis period. Table 3.1-2 shows the 16 possible integration variants for the booking process with their respective change to the net present value $\Delta NPV(\vec{d_j})$.

Table 3.1-2 Possible integration variants $\vec{\mathrm{d}}_\mathrm{j}$ and changes in net present value ΔNPVc(in €)

Integration variant $\vec{d_j}$ (customer integration in dark grey)		**-I$(\vec{d_j})$**	**ΔPE$(\vec{d_j})$**	**ΔCE$(\vec{d_j})$**	**ΔNPV$(\vec{d_j})$**
$\vec{d_1}$	p_1 – p_2 – p_3 – p_4 – p_5	0	0	0	0
$\vec{d_2}$	**p_1** – p_2 – p_3 – p_4 – p_5	-165,000	2,954,305	188,538	2,977,844
$\vec{d_3}$	p_1 – **p_2** – p_3 – p_4 – p_5	-465,000	6,706,678	471,346	6,713,024
$\vec{d_4}$	p_1 – p_2 – **p_3** – p_4 – p_5	-465,000	5,087,316	282,808	4,905,124
$\vec{d_5}$	p_1 – p_2 – p_3 – **p_4** – p_5	-465,000	-1,084,056	-235,673	-1,784,729
$\vec{d_6}$	**p_1** – **p_2** – p_3 – p_4 – p_5	-475,000	9,774,107	593,896	9,893,003
$\vec{d_7}$	**p_1** – p_2 – **p_3** – p_4 – p_5	-475,000	8,154,744	424,211	8,103,956
$\vec{d_8}$	**p_1** – p_2 – p_3 – **p_4** – p_5	-475,000	1,983,372	-164,971	1,343,401
$\vec{d_9}$	p_1 – **p_2** – **p_3** – p_4 – p_5	-475,000	11,907,118	678,738	12,110,856
$\vec{d_{10}}$	p_1 – **p_2** – p_3 – **p_4** – p_5	-475,000	5,735,746	117,836	5,378,582
$\vec{d_{11}}$	p_1 – p_2 – **p_3** – **p_4** – p_5	-475,000	4,116,383	-70,702	3,570,682
$\vec{d_{12}}$	**p_1** – **p_2** – **p_3** – p_4 – p_5	-485,000	14,974,546	848,423	15,337,969
$\vec{d_{13}}$	**p_1** – p_2 – **p_3** – **p_4** – p_5	-485,000	7,183,812	70,702	6,769,514
$\vec{d_{14}}$	**p_1** – **p_2** – p_3 – **p_4** – p_5	-485,000	8,803,174	240,386	8,558,560
$\vec{d_{15}}$	p_1 – **p_2** – **p_3** – **p_4** – p_5	-485,000	10,936,185	325,229	10,776,413
$\vec{d_{16}}$	**p_1** – **p_2** – **p_3** – **p_4** – p_5	-495,000	14,003,613	494,913	14,003,526

It becomes clear that integration variant $\vec{d}_{12}$, which yields a NPV increase of approximately € 15.34 million, is the optimal variant. Accordingly, the considered company should integrate its customers via SSTs in the sub-processes p_1 (information search), p_2 (entry of personal data) and p_3 (entry of travel data). Only the fourth sub-process "entry of accounting data" should be performed by the accounting assistants as knowledge is required, which the customers usually do not have. Analyzing the sensitivity of the model with respect to the estimated parameters influencing the determination of the support, we find that estimation errors do not change the optimal solution.

In contrast to that, the model of Heidemann et al. (2011), which does not explicitly determine the corresponding customer support, would generate the following results: Integration variant $\vec{d}_{16}$ is the optimal solution and yields a NPV of € 19.18 million. Thereby, the present value of investment outflows $I^{model\ of\ \text{(Heidemann,Kamprath,\& Müller,2011)}}(\vec{d}_{16})$ amounts to 415,000 and is lower than $I(\vec{d}_{12})$ as no go-live support is provided. The changes in cash flows for process operations $\Delta PE^{model\ of\ \text{(Heidemann,Kamprath,\& Müller,2011)}}(\vec{d}_{16})$ are 19,458,555 and so considerable higher then $\Delta PE(\vec{d}_{12})$ as no additional expenses for customer support are regarded. Finally, the indirect economic effects on customer behavior $\Delta CE^{model\ of\ \text{(Heidemann,Kamprath,\& Müller,2011)}}(\vec{d}_{16})$ are 141,404 and thereby smaller then $\Delta CE(\vec{d}_{12})$. According to the integration variant $\vec{d}_{16}$ the customers should additionally be integrated in the fourth sub-process. As mentioned above, performing this sub-process requires expertise and advanced knowledge on customers' side which can vary depending on the target customer group. If the customers do not possess this knowledge and do not get any support, they may avoid using the SST or be dissatisfied. Hence, the customers' ability and need for support also has to be considered in the decision model. Otherwise further expenses (e.g., costs for additional support or losings through customer churn), which were not taken into account by Heidemann et al. (2011) and which affect the calculated NPV negatively, will arise. Thus, not considering the target customer group and their need for support leads to false estimations of the related cash flows and thereby to another optimal solution.

This case illustrates that the economic decision model can be successfully applied in practice and that the parameters can be operationalized and determined. Nevertheless, it should be noted that the application of the model and, above all, the determination of the parameters can involve very substantial efforts and hence cause significant expenses. There are also some aspects of the case study that warrant critical discussion. For example, the analysis of the surveys revealed that the regarded customers have a comparatively favorable attitude towards technologies. This could be explained by the age group of the respondents (mainly 25 to 40 years) but does certainly not represent society. Hence, companies first have to investigate their customers' attitude towards technology and then they have to decide how they can deal with less technology-affine customers and how to motive them to use self-services. All the same, the main scientific contribution is the proposed quantitative economic decision model. This model allows for economically well-founded decisions when deciding on the implementation of SSTs by focusing on both the process perspective and the customer perspective; thus addressing the central dimensions of the impact of SSTs.

3.1.6 Conclusion

Current trends such as the emerging digitalization and the new self-understanding of the customers lead to an increasing use of self-services and enable customers to take part in the service delivery independent of direct involvement of an organization’s employee (Meuter et al., 2011). The challenge for companies to introduce SSTs successfully is to understand the effects of SSTs on customers. If customers do not feel comfortable with SSTs or have too little knowledge about how to use it, companies can facilitate the use of SSTs by offering customer support. For many companies the economic effects of SSTs and offering support are still unclear, and so decisions made without the necessary economic grounding. Therefore, this paper has presented a quantitative economic decision model that enables to evaluate the economic effects of self-services, while considering customer support. The model shows in which sub-processes customers should be integrated including additionally the expenses for the necessary customer support of each sub-process. In addition to that, we presented a possibility to calculate the customer support. Hence, our research complements prior research in the field of SSTs that considered only singular effects such as productivity and efficiency (Lovelock & Young, 1979) or customer satisfaction (Chow et al., 2008; Collier & Sherrell, 2010) as the predominant factors when deciding on customer self-service. The applicability of the model and its practical benefit have been illustrated by the example of a global travel solutions provider. Although this model pictures reality in a constrained way, it provides a basis for organizations to plan and improve their introduction and management of SSTs. Thereby, it is not only of high relevance to business practice, but also provides a theoretical approach to improve the quality of self-services for organizations and customers. We hope that our paper will stimulate further research on that fascinating topic and will serve as a proper starting point for future works.

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3.2 Between death and life – a formal decision model to decide on customer recovery investments

Abstract

As digitization supports customers in gaining increased market transparency (Desai 2014), migrating from one organization to another ("customer migration") is becoming easier and more attractive. Thus, taking measures to regain customers who terminated their relationship ("customer recovery") has become increasingly important for organizations. With the growing importance of customer recovery in present times, organizations face even more challenges pertaining to risk of making wrong investment decisions. Organizations can either mistakenly invest in customer relations that are "alive" or irretrievably "dead." Furthermore, it has the risk of not investing in inactive customer relations that have a chance to be revived ("dying"). Consequently, it is necessary for organizations to consider the probability that a customer relation is "alive," "dying," or "dead" when deciding on customer recovery. Based on these probabilities, an economically reasonable decision has to be made on whether to invest in the recovery of an individual customer relationship. Accordingly, based on a comprehensive discussion of related work, we propose a formal decision model on whether to invest in customer relation recovery. To demonstrate the decision model's applicability, an illustrative case with sample calculation is presented and expert interviews are conducted.

Keywords: Customer data, Customer recovery, Digitization, Decision model

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3.2.1 Introduction

In all types of organizations, customers may come and go. As stated by Schmittlein et al. (1987), there are customers who are “alive” (i.e., maintain an active customer relation) and customers who are “dead” (i.e., left the organization for some reason). Moreover, these “dead” customers should be further segmented as organizations adopt different strategies in the customer recovery for these two kinds of customers (Griffin & Lowenstein, 2001). In this paper, we segment this “dead” customers into “dying” and “dead”. Thereby, “dying” customers are those whom the organization wants to recover (e.g., inactive customers who are unintentionally pulled or pushed away), whereas “dead” customers represent the ones on whom customer recovery is not reasonable (e.g., unprofitable customers, customers with changing needs due to changing demographics) (Griffin & Lowenstein, 2001). With digitization, which can be defined as the use of digital technologies to improve or disrupt business models and provide new value-producing opportunities (Gartner, 2016), as a main driver for the global economy, making the distinction between “alive,” “dying,” or “dead” customers is becoming more and more challenging. Hence, customer migration becomes easier and more attractive as digitization is breaking down the barriers of entry, enabling more transparent markets, and becoming comparatively impersonal (Desai, 2014). Therefore, the importance of managing customer recovery is increasing. Most organizations neglect customer recovery and focus on customer acquisition and retention, although an average organization loses 20 to 40 percent of its trade due to defecting customers (Griffin & Lowenstein, 2001). This challenge intensifies in settings where customers are not bound by contracts and have the possibility to alter between different vendors (Dwyer, 1989; Reinartz & Kumar, 2000). On the other hand, digitization not only amplifies customer migration, but also benefits organizations because of the significant increase in the availability of customer data (Mayer-Schönberger & Cukier, 2013). Consequently, with the increasing amount of available data, opportunities to identify customer insights from data continue to expand. Organizations have the possibility to collect, store, and analyze available customer data (Beath et al., 2012) and use it for making custom-designed investment decisions in the recovery of individual customer relations as well as other purposes.

The related literature already provides models for deciding between different marketing investment alternatives (Neslin et al., 2013; Rust et al., 2004). It also develops guidelines for retention decisions (Blattberg et al., 2001; Blattberg & Deighton, 1996). However, although economic aspects such as cost-benefit-trade-offs are investigated in the extant literature, the customer relations for which an investment is actually required is not always clear. For instance, it would not be reasonable to invest in recovering a customer relation that is active and is likely to realize further transactions anyway. However, as the point at which a customer relation becomes inactive cannot always be known for sure, it has to be estimated using indicators such as low number of transactions or unexpectedly long time since the last transaction (Schmittlein et al., 1987). Therefore, whether a customer relation is “alive” or “dead” can be estimated as a conditional probability, given certain purchase information (Schmittlein et al., 1987).

To summarize, organizations are faced with challenges in estimating the probability of a customer relation being “alive,” “dying,” or “dead,” which in turn, determines the probability at which an investment in the recovery of an individual customer relation is economically reasonable. However, in extant literature there is no approach that observes the economic feasibility of customer recovery investments while considering these probabilities that a customer relation is “alive,” “dying,” or “dead.” Therefore, we address the following research question in the paper: How can an organization decide on investing in a customer relation on the basis of the probability of a customer relation “dying”? To answer this question, we develop a formal decision model, in which we compute a threshold, at which an investment in an individual customer relation is economically reasonable, considering the probability of a customer relation being “alive,” “dying,” or “dead.” Thereby, investing in the recovery of a customer relation is reasonable only when the present value of future cash flow when investing in the recovery of a customer relation is higher compared to when not investing.

We start the paper with a discussion of the context of the problem with reference to related work to provide a theoretical background. Then, we propose the decision model and demonstrate its application using a sample calculation. After that, we present the current status of practice and evaluate its practicability and acceptability in practice by conducting expert interviews. Finally, we discuss the resulting decision model.

3.2.2 Theoretical background

3.2.2.1 “Alive,” “dying,” and “dead” customers

Digitization makes customer focus more valuable as well as a big challenge for organizations with customer migration becoming easier and more attractive than before (Rezabakhsh et al., 2006). In this environment, organizations not only need to acquire new customers and build loyalty among existing customers, but also target migrated customers (Strauss & Friege, 1999; Thomas et al., 2018). Typically, customer migration arises as soon as there is a gap between the priorities of the customer and the activities of the organization (Kotler, 2004). From an organization's perspective, the reasons for such a gap can be manifold: the lack of success in identifying and using interesting market opportunities, limited information about competitors, no effective communication with the market, no comprehensive customer service, or missing knowledge about customer needs, their perceptions, preferences, and behavior (Czarniewski, 2014). In summary, to avoid customer migration, organizations need to increase customer satisfaction as it affects customers' repurchase likelihood (Auh & Johnson, 2005; Strauss & Friege, 1999). Customer satisfaction can, for instance, be defined as a cumulative evaluation of a customer's purchase and consumption experience to date (Auh & Johnson, 2005; Johnson et al., 1995; Lervik & Johnson, 2003; Rust et al., 1995). Generally, customers are considered "alive" as long as they are maintaining an active relation with the organization, and "dead" if they have terminated their relation with the organization for whatever reason (Schmittlein et al., 1987).

To recover "dead" customer relations, an organization needs to first identify the respective customers. At first glance, determining whether a customer relation is "dead" or "alive" seems obvious. For instance, if customers cancel their cell-phone contract and change their provider, the customer relation would clearly be considered "dead." In contrast, there are situations wherein a customer relation transition from being "alive" to being "dead," which is not always that easy for organizations to detect, as customers "may not notify the firm when they leave" (Schmittlein et al., 1987). This holds true for hotel stays, air travel, or large online retailers such as Amazon, where customers are not bound by contracts and have the possibility to switch between different vendors (Dwyer, 1989; Reinartz & Kumar, 2000). Hence, particularly in non-contractual customer relations, it is a challenge for organizations to know whether a customer relation is "alive" or "dead" (Schmittlein et al., 1987). One indicator for organizations to determine whether a customer relation is "alive" or "dead" is a customer's purchasing information (e.g., an unexpectedly long time period since the last transaction) (Fader et al., 2005). However, a long transaction break does not necessarily imply that a customer relation is definitively "dead" (Fader et al., 2005). Generally, the related literature approaches this topic of segmenting customers by modeling customer migration. Several researchers use recency in models that predict customer behavior. For example, Bult and Wansbeek (1995), Bitran and Mondschein (1996), Fader et al. (2005), and Rhee and McIntyre (2008) find a negative association between recency and purchase likelihood. Dwyer (1997) identifies "always-a-share" customers' purchase probability by developing a purchase decision-making tree based on historical buying data. The Dwyer model is used in most customer lifetime value (CLV) research (Qi et al., 2006). CLV, which is defined as the net present value (NPV) of the customer's profitability throughout the customer relationship, is a central profitability metric for analyzing customer relations (Dwyer, 1989; Thomas et al., 2018). For instance, comprehensive explanations of CLV can be found in Kumar and Reinartz (2012). Blattberg et al. (2001) extend the Dwyer model and use the "recency, frequency, monetary index" to develop the purchase decision-making tree (Qi et al., 2006). In brief, the extant literature has long contributed to the understanding of customer migration and the factors affecting it.

Nevertheless, not all of the "dead" customers have win back potential. Moreover, the organization does not want to recover them all. Hence, it is essential for organizations to distinguish the "dead" customers based on their win back potential to avoid wasting a lot of time and money on recovering lost customers with poor prospects for future business. Strauss and Friege (1999) provide a more detailed classification of "dead" customers. They develop a conceptual basis for customer recovery with the objective of winning back "dead" customers. Therefore, they classify "dead" customers into five categories: intentionally pushed-away customers, unintentionally pushed-away customers, pulled-away customers, bought-away customers, and moved-away customers. Organizations have no interest in continuing relations with intentionally pushed-away customers as these relations have a negative expected cash flow or a high risk of bad debt, and thus are not economical. Bought-away customers, who switch to the competitor for better prices, and moved-away customers, who move away physically or have changing needs, can only be regained with high effort and expensive investments. As such, only the customers in the categories unintentionally pushed-away and pulled-away should be targeted by the organizations (Strauss & Friege, 1999). Unintentionally pushed-away customers leave the organization due to their dissatisfaction with the service provided or the feeling of being taken for granted (Griffin & Lowenstein, 2001). On the other hand, pulled-away customers migrate as they expect better personal service or higher product quality (Griffin & Lowenstein, 2001). To summarize, we can differentiate between "dead" customers, which represent the ones from whom recovery is unreasonable (e.g., intentionally pushed-away customers) and "dying" customers, that is, those whom the organization wants to recover (e.g., unintentionally pushed-away and pulled-away customers) (Griffin & Lowenstein, 2001).

3.2.2.2 Customer recovery investments

Customer recovery campaigns are a specific kind of customer campaign. According to the campaign management process of Englbrecht (2007), campaigns are mainly characterized by target group, channel, and content. Hence, investment decisions are to be made between different campaign alternatives comprising possible target groups, channels, or content. Here, the target group comprises migrated customers, or in other words “dying” customer relations. Channels, for instance, are categorized into offline channels, such as stores or catalogs, and online channels, such as mobile apps, email, or websites. They can also be differentiated on the basis of direct and indirect channels, that is, whether there is an intermediary responsible for managing the relationship between the customer and the organization (Hosseini et al., 2015). Typically, the content of customer recovery campaigns can entail marketing investments, like special offers, discounts, vouchers, coupons, or other incentives for recovering customer relations.

As regards deciding on competing marketing investments, the extant literature provides numerous approaches. For example, Rust et al. (2004) provide a framework to trade off competing marketing investments on the basis of financial return. Neslin et al. (2013) demonstrate how to target to the right customers with the right marketing at the right time considering the customer’s recency state to maximize CLV. Venkatesan and Kumar (2004) recommend CLV as a metric for selecting customers and designing marketing programs, as they provide empirical evidence to support the existence of a relationship between marketing actions and CLV. As such, Glady et al. (2009) suggest that the dependence between the number of transactions and their profitability can be used to increase the accuracy of the CLV. Venkatesan and Kumar (2004) point out that the extant literature provides guidelines for acquisition and retention decisions (Blattberg et al., 2001; Blattberg & Deighton, 1996). There are also studies on the basis of which customers are to be “eliminated.” For instance, Reinartz and Kumar (2003) demonstrate how to determine whether to terminate a customer relation. However, when addressing customer recovery, the CLV is not the metric of interest, as the second lifetime value (SLTV) focuses on the NPV generated by the customer after the recovery Strauss and Friege (1999). With regard to the development and implementation of a customer recovery program, the expected future value of the recovered customer should be the central factor that guides the decision on the customers who need to be recovered (Strauss & Friege, 1999). In summary, the extant literature provides various discussions and models concerning investments in customer relations (see Table 3.2-1). However, to the best of our knowledge, there is no formal decision model on the economic feasibility of customer recovery investments while considering the probabilities that a customer relation is “alive,” “dying,” or “dead.” Thereby, the consideration of this probability is crucial in order to make economically reasonable customer recovery decisions, as errors in distinguishing “alive” and “dead” customer relations can be avoided.”

Table 3.2-1 Summary extant literature

Study	Nature of Study
Rust et al. (2004)	Framework to trade off between competing marketing investments
Neslin et al. (2013)	Approach to target an organization’s marketing efforts, keeping in mind the customer’s recency state.
Venkatesan and Kumar (2004)	Framework to allocate marketing resources efficiently across customers and channels of communication
Glady et al. (2009)	Approach for predicting the CLV considering the dependence between the number of transactions and profitability
Reinartz and Kumar (2003)	Framework to measure the profitable lifetime duration
Strauss and Friege (1999)	Conceptual basis aiming at winning back customers who left an organization

To fill this gap, we introduce a calculation to identify the most economically reasonable investment alternative among multiple customer recovery investments and propose a decision model that gives advice on whether to invest in customer recovery. Based on an existing decision model designed to manage data currency (Görz, 2011), we propose our model on the probability that a customer relation is “dying.” The detailed decision model is described in the subsequent chapter.

3.2.3 Decision Model

The basic idea of the model is to make a decision for every customer on investing in customer recovery by comparing a threshold at which an investment is economically useful to the current probability of a customer relation “dying.” Moreover, the decision model considers that organizations should not invest in “dead” customers who have finally migrated for reasons like moving away, having new demands and needs, getting involved in a legal dispute with the organization, or physical death. The threshold depends on investment specific variables, such as the costs of the investment and an effectiveness factor, and customer specific ones, such as the present value of future cash inflows of a customer relation. Besides that, we make certain assumptions for our decision model. First, we assume that the decision model is designed to cover a single period. Second, the organization’s risk attitude is neutral when deciding on customer recovery investments. Third, we exclude the fact that it can be advantageous for organizations to invest in "dead" customers to minimize the negative effects of dissatisfied customers (Stauss & Seidel, 2004).

The decision model has four steps: Step 1 is "selection of the most economically reasonable investment alternative." This describes how an organization, which has various options for investing in customer recovery (for instance, different channels, such as letter or email, or different contents, such as vouchers and special offers) can determine the most economically reasonable investment alternative for customer recovery. Step 2 is "measuring the probabilities of a customer relation being "alive," "dying," or "dead" is necessary. These probabilities, in conjunction with the threshold, which is deduced in step 3 "derivation of the threshold," are the basis to make an economically reasonable investment decision for customer recovery. Lastly, step 4 is "making the investment decision." This indicates how the organization can make this decision by comparing the probability that the customer relation is "dying" with the threshold.

Step 1: Selection of the most economically reasonable investment alternative

The organization has to decide between several investment alternatives for customer recovery. For each customer, a specific investment alternative j $(j = 1, \dots, m \; with \; m \in \mathbb{N})$ can be the most economically reasonable. The decision underlies the expected cash flow $E(CF_{ij}) \in \mathbb{R}_0^+$ of a customer relation i $(i = 1, \dots, n \; with \; n \in \mathbb{N})$ when successfully recovering it with a specific investment alternative j $(j = 1, \dots, m \; with \; m \in \mathbb{N})$. To calculate $E(CF_{ij})$, the present value of future cash inflows of a customer relation $\pi_i \in \mathbb{R}^+$, the investment costs $I_j \in \mathbb{R}^+$, of a specific investment alternative j and the effectiveness factor $\eta_{ij} \in (0; 1]$, which determines the success probability of a recovery investment alternative j for a customer relation i , as they all influence the economic assessment of the investment alternatives. The domain of π_i is defined as $\mathbb{R}^+$, as only customers with positive cash flows are of interest for an organization. The domain of η_{ij} excludes the value 0, as we exclude investment alternatives for which customer recovery is impossible. Additionally, investments in customer relations with negative expected cash flows $E(CF_{ij})$ are not economically reasonable. Therefore, $E(CF_{ij})$ is only defined for $\pi_i \cdot \eta_{ij} - I_j \geq 0$. Hence, the calculations represented by Equation 1 lead to the economically optimal investment alternatives J_i^*. In general * indicates the respectively optimal result.

$$J_i^* = \{j \in (1, \dots, m); \forall k \in (1, \dots, m)\backslash\{j\} : E(CF_{ik}) \leq E(CF_{ij})\},$$
$$\text{with } E(CF_{ij}) = \pi_i \cdot \eta_{ij} - I_j, \tag{1}$$

where J_i^* represents the set of all investment alternatives with the indices j for which the expected cash flow $E(CF_{ij})$ of a customer relation i for a specific investment alternative j is maximal compared to the expected cash flows $E(CF_{ik})$ of the other possible investment alternatives k ($k = 1, \dots, l \; with \; l \in \mathbb{N}$). In case of multiple resulting indices j for J_i^*, that is, indices j with the same expected cash flows, $E(CF_{ij})$, the one making the decision should choose the investment alternative j that is cheaper after normalization for effectiveness (e.g., if $J_i^* = \{1,2\}$ and $I_1 < I_2 \cdot \frac{\eta_{i1}}{\eta_{i2}}$, then decide for $j = 1$). Normalization is necessary for the case of unproportional investment costs I_j, compared to the effectiveness factor η_{ij}.

Step 2: Measuring the probabilities of a customer relation being "alive," "dying," or "dead"

In the following, we use the model for assessing conditional probability of Schmittlein et al. (1987) as a basis for estimating the probability that a customer relation i is "alive." According to Fader and Hardie (2009), the model of Schmittlein et al. (1987) indicates an impressive predictive performance, its empirical validation is often presented, and there are several applications in different contexts, such as customer profitability, churn prediction, and customer base analysis (Fader et al., 2005; Hopmann & Thede, 2005; Reinartz & Kumar, 2000, 2003; Schmittlein & Peterson, 1994; Wübben & Wangenheim, 2008; Zitzlsperger et al., 2007). The conditional probability $P_i("alive"|Information) \in [0;1]$ depends on a customer's individual purchasing information (Schmittlein et al., 1987). This can be $Information = x, t_x, T$, where x is the number of transactions observed in the time interval $(0, T]$ and $t_x (0 < t_x \leq T)$ is the time of the last transaction (Schmittlein et al., 1987). This implies that recency and frequency are sufficient statistics for an individual customer's purchasing behavior (Fader et al., 2005).

Besides discerning a customer as being "alive," customers can also be classified as "dying," which is denoted in the decision model with probability $P_i("dying"|Information) \in [0;1]$. These customers are dormant, but can be made active again. Hence, the organization should invest in them (Griffin & Lowenstein, 2001).

However, not all customers who are not "alive" can be recovered. There are customers who will never return as well as those that the organization does not want to win back (Griffin &

Lowenstein, 2001). Therefore, it is a prerequisite for organizations to distinguish between the "dying" and the "dead." This allows them to divide those customers who are not "alive" into those with recovery potential and those without. In the absence of such a distinction the organization can lose a lot of time and money on investing in customers who are "dead" and have no prospects of recovery (Griffin & Lowenstein, 2001). The probability $P_i("dead"|Information) \in [0;1]$ also depends on the individual purchasing information of every customer i, like the number of transactions or the time of the last transaction. With the two probabilities $P_i("alive"|Information)$ and $P_i("dead"|Information)$ the organization can determine the missing probability $P_i("dying"|Information)$, which needs to be compared to the threshold to make an economically reasonable investment decision.

$$\begin{gathered} P_i("dying"|Information) = \\ 1 - P_i("alive"|Information) - P_i("dead"|Information) \end{gathered} \tag{2}$$

Step 3: Threshold derivation

As it is highly improbable to know for sure if a customer relation is "alive," "dying," or "dead," there is always the possibility that the organization comes to a "correct" or "wrong" investment decision for a customer relation i. As far as the "wrong" investment decisions are concerned, the organization can commit two types of errors. The type I error represents the "wrong" decision, i.e., an organization does invest in customer relations although customer relation recovery would not be necessary. Accordingly, the cases Ia (the organization unnecessarily invests in "dead" customer relations) and Ic (the organization unnecessarily invests in customer relations that are "alive"), which are illustrated in Table 3.2-2, represent the type I errors in the decision model. As opposed to this, not investing in a customer relation that will end without this investment shows the type II error. In Table 3.2-2, this error type refers to the case Ib (the organization does not invest in "dying" customer relations although there would be positive expected cash flows in case of customer relation recovery). By taking such "wrong" decisions, the organization either incurs unnecessary costs on investment or loses cash inflows that might result from investment j. Accordingly, cases IIa, IIb, and IIc represent "correct" decisions as long as $\pi_i \cdot \eta_{ij} \geq I_j$. Even if we assume for our decision model that the organization's risk attitude is neutral when deciding on customer recovery investments, we briefly discuss the effects of the potential decisions of a risk-averse and a risk-aware decision-maker. A risk-averse organization tends to invest comparatively more in customer recovery in order to minimize the risk of migrating customers and losing expected payments. As a result, such an organization is more likely to invest in customer recovery than a risk-tolerant one. Consequently, a risk-tolerant decision-maker will tend to invest less in customer recovery as he is more willing to risk the customer migration. In summary, one can say that a risk-averse organization is more likely to make the type I error, while a risk-tolerant organization commits the type II error.

Table 3.2-2 represents all possibilities of total expected cash flows depending on the probabilities $P_i("dead"|Information)$, $P_i("dying"|Information)$, and $P_i("alive"|Information)$ and the decisions to invest in customer relations or not.

Table 3.2-2 Matrix of the total expected cash flow

Decision	***"Dead"*** $\boldsymbol{P_i("dead"|Info.)}$	***"Dying"*** $\boldsymbol{P_i("dying"|Info.)}$	***"Alive"*** $\boldsymbol{P_i("alive"|Info.)}$
Investment	Ia $-I_j$	IIb $\pi_i \cdot \eta_{ij} - I_j$	Ic $\pi_i - I_j$
No investment	IIa 0	Ib $-\pi_i \cdot \eta_{ij}$	IIc π_i

The total expected cash flow in case Ia represents the investment cost I_j, which is unnecessarily incurred as the customer relation is "dead" with no prospects of recovery. These costs incurred on unnecessary investments in customer recovery are represented by Equation 3. Thereby, the symbol "∧," which is the logical connective with the meaning "AND," means that the expected cash flow $E(CF_{ij})$ in case of Ia only occurs if the organization decides to implement an investment "AND" customer is "dead".

$$E(CF_{ij})(investment \wedge "dead") = -I_j. \tag{3}$$

Case Ib, which arise in case the organization decides to not invest in a "dying" customer, leads to lost present value of future cash inflows $-\pi_i$ caused by the inability to recover this customer relation i. This lost present value of future cash inflows, which corresponds to opportunity costs, only comes into force to the extent to which the customer recovery investment would have been successful, which is represented by the effectiveness factor η_{ij} (see Equation 4).

$$E(CF_{ij})(no\ investment \wedge "dying") = -\pi_i \cdot \eta_{ij}. \tag{4}$$

The total expected cash flow of case Ic indicates the present value of future cash inflows $\boldsymbol{\pi_i}$ resulting from a customer relation i minus the investment costs I_j of investment alternative j for investing in an "alive" customer relation (see Equation 5). Here, the investment costs I_j are unnecessarily incurred as customer recovery is ineffective.

$$E(CF_{ij})(investment \wedge "alive") = \pi_i - I_j. \tag{5}$$

Case IIa indicates the correct decision of an organization to not invest in a “dead” customer. This decision results in a total expected cash flow equal to 0, as no investment is made and the customer generates no future cash inflows (see Equation 6).

$$E(CF_{ij})(no\ investment \wedge "dead") = 0. \tag{6}$$

Given $\pi_i \cdot \eta_j \geq I_j$, investing in a “dying” customer relation (case IIb) and not investing in a customer relation that is “alive” one (case IIc) are correct decisions. Hence, case IIb entails the present value of future cash inflows of a customer relation π_i multiplied by the effectiveness factor η_{ij} less the costs of investment I_j (see Equation 7).

$$E(CF_{ij})(investment \wedge "dying") = \pi_{\boldsymbol{i}} \cdot \eta_{ij} - I_j. \tag{7}$$

Case IIc represents not investing in a customer relation that is “alive,” which results in the present value of future cash inflows $\pi_{\boldsymbol{i}}$ (see Equation 8).

$$E(CF_{ij})(no\ investment \wedge "alive") = \pi_i. \tag{8}$$

Based on these mathematical terms (see Equation 3-8), the threshold for an economic decision on whether to invest in a customer relation can be deduced. From an economic point of view, investing in a customer relation is only reasonable if the total expected cash flow in case of an investment for recovering a customer relation is higher than the total expected cash flow for not investing (see Inequation 9). The cases Ia, Ib, Ic, IIa, IIb and IIc arise with the probabilities that a customer relation i is already “dead” $P_i("dead"|Information)$, “dying” $P_i("dying"|Information)$, and “alive” $P_i("alive"|Information)$, as presented in Table 3.2-2. Inequation 9 covers decisions under risk neutral preferences:

$$\begin{gathered}
E(CF_{ij})(investment \wedge "dead") \cdot P_i("dead"|Information)\ + \\
E(CF_{ij})(investment \wedge "dying") \cdot P_i("dying"|Information)\ + \\
E(CF_{ij})(investment \wedge "alive") \cdot P_i("alive"|Information)\ > \\
E(CF_{ij})(no\ investment \wedge "dead") \cdot P_i("dead"|Information) + \\
E(CF_{ij})(no\ investment \wedge "dying") \cdot P_i("dying"|Information) + \\
E(CF_{ij})(no\ investment \wedge "alive") \cdot P_i("alive"|Information).
\end{gathered} \tag{9}$$

After substituting the Equations 3–8 in Inequation 9, we solve the inequality for $P_i(\text{"}dying\text{"}|Information)$ (see Inequation 10), which results in the threshold $T_{ij} \in [0;1)$:

$$T_{ij} < P_i(\text{"}dying\text{"}|Information), \qquad (10)$$

$$with\ T_{ij} = \frac{I_j}{2\pi_i\eta_{ij}}.$$

The threshold enables organization to make investment decisions wherein the total expected cash flow from an investment in recovering a customer relation is higher than that from not investing.

Step 4: Making the investment decision

To make the investment decision D_i for a customer relation i, the organization should now compare the probability that the customer relation is "dying," $P_i(\text{"}dying\text{"}|Information)$, with the threshold T_{ij}:

$$D_i = \begin{cases} invest & for\ T_{ij} < P_i(\text{"}dying\text{"}|Information) \\ not\ invest & for\ T_{ij} \geq P_i(\text{"}dying\text{"}|Information) \end{cases}. \qquad (11)$$

In summary, the four proposed steps lead to an economically reasonable decision on whether to invest in the recovery of an individual customer relation by comparing the threshold to the current probability of a customer relation being "alive," as per Inequation 11.

3.2.4 Evaluation

To demonstrate the decision model's practicability, we first present an illustrative case with a sample calculation and sensitivity analysis. Subsequently, the results of the interviews with experts from its practice are presented.

Application of the decision model

We illustrate the applicability, completeness, understandability, feasibility, and operationality of the decision model with an example in which an online retailer aims at recovering possibly "dying" customer relations. At the same time, the online retailer wants to avoid unnecessarily investing in customer relations that are either "dead" or "alive." By using our decision model, the online retailer addresses only those customer relations for which an investment is reasonable on the basis of the probability that they are "dying" relative to the calculated threshold. As such, we demonstrate the economic benefit of the decision model.

Step 1: Selection of the most economically reasonable investment alternative

At first, the online retailer has to identity different investment alternatives for customer recovery and then, has to select the most economically reasonable investment alternative for every customer relation i. In our example, the online retailer selects four possible investment alternatives j, that is, two different channels, letter and mail, and two different contents, voucher and special offer. According to the experience of the online retailer, customer recovery via letter is more effective than via email. Similarly, a voucher is more effective than a special offer. Moreover, in this example, customer recovery through vouchers requires more investment costs than special offers. Table 3.2-3 presents the effectiveness factor η_{ij} and the costs of the four investment alternatives I_j.

Table 3.2-3 η_{ij} and I_j for the investment alternatives

		Special offer via letter ($\boldsymbol{j=1}$)	***Voucher via letter*** ($\boldsymbol{j=2}$)	***Special offer via email*** ($\boldsymbol{j=3}$)	***Voucher via email*** ($\boldsymbol{j=4}$)
$\boldsymbol{\eta_{ij}}$	$i=1$	0,15	0,17	0,10	0,15
	$i=2$	0,03	0,07	0,05	0,14
	$i=3$	0,08	0,10	0,06	0,03
$\boldsymbol{I_j}$		USD 20	USD 30	USD 12	USD 22

To select the most economically reasonable investment alternatives for different customers according to Formula 1, we take the present values of future cash inflows π_i of three customers; for example, $\pi_1 = USD\ 214$, $\pi_2 = USD\ 886$, and $\pi_3 = USD\ 780$. Table 3.2-3 presents the expected cash flows, calculated as described in Formula 1 ($E(CF_{ij}) = \pi_i \cdot \eta_{ij} - I_j$), for each customer relation i and the four different investment alternatives j.

Table 3.2-4 $E(CF_{ij})$ for the customer relations and investment (USD)

		Investment alternatives			
		$j=1$	$j=2$	$j=3$	$j=4$
Customer Relations	$i=1$	**11.69**	7.01	10.25	10.23
	$i=2$	5.74	36.21	29.38	**100.72**
	$i=3$	45.92	**48.42**	33.83	2.41

The results of Table 3.2-4 indicate that the most economically reasonable investment alternative for the customer relation $i = 1$ is $j = 1$, for $i = 2$ is $j = 4$, and for $i = 3$ is $j = 2$ (see bold marked values in Table 3.2-4), as these investment alternatives have the greatest expected cash flow for different customers, as per Equation 1.

Step 2: Measuring the probability of a customer relation "dying"

Next, the online retailer has to quantify the probability of a customer relation "dying," that is, $P_i("dying"|Information)$, according to Equation 2. For example, we assume the following values for the three customers: $P_1("dying"|Information) = 0.36$, $P_2("dying"|Information) = 0.31$, and $P_3("dying"|Information) = 0.16$.

Step 3: Threshold derivation

Further, the online retailer has to calculate the threshold for the customers and the selected investment alternative by using Inequation 10.

Table 3.2-5 Results of the threshold T_{ij}

	$\boldsymbol{J_1^* = 3}$	$\boldsymbol{J_2^* = 4}$	$\boldsymbol{J_3^* = 2}$
$\boldsymbol{T_{ij}}$	31.56%	8.96%	19.13%

Step 4: Making the investment decision

The application of Inequation 11 indicates whether the online retailer should invest in the customer relations or not by comparing the threshold T_{ij} with the probability of the customer relation i "dying," $P_i("dying"|Information)$.

Table 3.2-6 Investment decision for customer relations $\boldsymbol{i}$

			$\boldsymbol{D_i}$
$\boldsymbol{i = 1}$	T_{11}	31.56%	invest
	$P_1("dying"|Information)$	36.00%	
$\boldsymbol{i = 2}$	T_{24}	8.96%	invest
	$P_2("dying"|Information)$	31.00%	
$\boldsymbol{i = 3}$	T_{32}	19.13%	not invest
	$P_3("dying"|Information)$	16.00%	

Table 3.2-6 indicates that the online retailer should invest in customer relation $i = 1$ and $i = 2$ because the results of the threshold T_{11} and T_{24} are less than

$P_1(\text{"}dying\text{"}|Information)$ and $P_3(\text{"}dying\text{"}|Information)$, respectively. For customer relation $i = 3$ the investment decision is not to invest, as T_{32} is greater than $P_3(\text{"}dying\text{"}|Information)$.

3.2.4.1 Evaluation of Decision Model

Next, we explain why the evaluation criterion is fulfilled. First, applicability is indicated by conducting this example calculation. Further, this evaluation type demonstrates the completeness of the decision model's as all input variables are quantitative measures and comprehensive. The evaluation criterion understandability is shown as the actual measure is easy to interpret and the model is easily applicable by users. Feasibility and operationality is given as the parameters are determinable, well defined, and indicate that the decision model is based on a quantitative measurement. Additionally, the data necessary for the decision model are accessible and affordable because the number of transactions or the time of the last transaction is usually known by the organizations. To evaluate the decision model from an economic perspective, we extend the sample calculation and instantiate the decision model with 10,000 customer relations that have equally distributed probabilities of "dying" in an interval of 0–100% and equally distributed expected cash flows in an interval of USD 0–1,000. The effectiveness factors of the investment alternatives are equally distributed in an interval of 0–20%. In this sample calculation, we use the parameter setting of the four investment alternatives listed in Table 3.1-2. In case of a perfect estimation of the probability of customer relations "dying," $P_i(\text{"}dying\text{"}|Information)$, the sample calculation reveals that about 20% of the individual recovery investments can be reduced by applying the decision model, which leads to significant cost savings. As depicted in Table 3.2-7, according to a sensitivity analysis, on one hand, estimation errors of one of the effectiveness factor η_{ij} only lead to disproportionately low changes in cost savings (e.g., an estimation error of -20% of the effectiveness factor η_{ij} leads to a change of 2% in the cost savings). That is, the model can be considered as being robust in terms of this parameter.

Table 3.2-7 Impacts of estimation errors on cost savings

Parameter estimation error	**-20%**	**-15%**	**-10%**	**-5%**	**0%**	**+5%**	**+10%**	**+15%**	**+20%**
η_{ij}	2%	2%	1%	0%	0%	-1%	-1%	-2%	-3%
$E(CF_{ij})$	7%	5%	4%	2%	0%	-5%	-8%	-13%	-17%
$P_i(\text{"}dying\text{"}|Inf.)$	29%	19%	13%	6%	0%	-6%	-11%	-16%	-22%

On the other hand, the sensitivity analysis exposes that $P_i("dying"|Information)$ and the expected cash flows $E(CF_{ij})$ need to be estimated carefully, as estimation errors lead to disproportionately high changes in cost savings (e.g., an estimation error of -20% of the expected cash flows $E(CF_{ij})$ leads to a change of 7% in cost savings and an estimation error of -20% of $P_i("dying"|Information)$ leads to a change of 29% in cost savings). However, even with poorer estimations, savings on a low percentage basis can be generated, which can easily be significant in monetary terms for large customer recovery investments.

3.2.4.2 Expert Interviews

To evaluate the practical applicability of the decision model and to give recommendations for action, seven experts experienced in science and business practices were interviewed. Therefore, we adopted the approach of theoretical sampling from the grounded theory methodology (Glaser & Strauss, 1967). In detail, we selected the experts stepwise in order to get a heterogeneous interviewees and organizations. In this way, we aim to examine and analyze as many aspects of the model as possible. The experts are active in different fields of work and their respective organizations operate in different sectors (e.g., financial service, automobile, IT, and tourism), have different legal forms (e.g., limited and corporation), and different number of employees (from less than 10 to more than 100,000) (see Table 3.2-8). Furthermore, two experts work with start-ups, whereas five of them work for established organizations. These facts show the diversity of the organizations included in our sample. The interviews were conducted in Germany and each interview lasted approximately 45 minutes, was semi-structured and guideline-based, and conducted via telephone. The interviews were recorded and replayed multiple times in order to strengthen the evaluation of the decision model. Semi-structured interviews enable the respondents to think and reflect upon the issues, their experiences, and new ideas and perspectives (Kramp, 2004). The interview was divided into two parts. First, the experts were asked for detailed explanations on the current status of practice, whether their organizations explicitly carry out customer recovery investments, how they manage customer recovery in general, the basis on which they arrange customer recovery investments, and whether they use decision models in their investment decisions. The second part of the interview contained questions on the applicability of the model in a real-world context, the availability of relevant data in the organizations, and the way the experts could make a decision with the help of the model. For evaluating the decision model, we used an approach sourced from the grounded theory methodology, namely constant comparison (Glaser & Strauss, 1967). With that, it is possible to constantly compare the findings from preceding interviews with subsequent ones during the overall interview process to improve the validity of the findings. The goal is to detect similarities and discover patterns (Tesch, 1990) The similarities and insights that were identified are summarized as follows.

Table 3.2-8 Sectors, legal forms, and the number of employees in the organizations of the interviewed experts

Expert	Job description	Sector	Legal form	Number of employees
A	Project Manager	Financial service	Limited	500-1000
B	CRM Expert	Automobile	Corporation	>100.000
C	Head of Marketing and Operation	IT (Startup)	Limited	10-50
D	Executive assistant	Financial service	Corporation	>100.000
E	CEO	Tourism	Limited	10-50
F	CEO	Automobile	Limited	10-50
G	Development manager	Financial service (Startup)	Corporation	<10

Expert interviews on the current status of practice

All the experts emphasized the importance of customer recovery and its active management. Expert A particularly highlights this with the fact that customer recovery is significantly more profitable than the acquisition of new customers. Thus, it is hardly surprising that all of the expert interviews indicate that the involved organizations implement customer recovery management. However, they do not manage it in the same way. According to experts B and D, in long-established, large corporations, customer recovery management is conducted decentrally through the sales departments and agencies and is not centrally managed by the organizations' headquarters. One reason for doing so is the lack of a uniform database and a customer relationship management (CRM) system. The customer data belong to the sales departments and agencies, which maintain a traditional customer relation with direct customer contact. From a regulatory perspective the organizations' headquarters do not have the permission to contact the customers for recovery. The decentralized customer recovery management of the sales departments and agencies requires customer recovery to be managed individually and not across the organization. As a result, no control or quality assurance of the measures can be ensured, and thus, the success of the customer recovery management depends on the agencies. The aim of these organizations is to introduce centralized customer data management to enable uniform decision-making that combine the objectives of the organizations' headquarters with those of the sales and branch offices using predictive data analysis and big data. Expert D emphasizes that the awareness of the use of data analysis is in practice, but this is often used at a very rudimentary level. In contrast, young organizations, like the organizations of experts A, C, and G, whose business model is fully digitized, are able to use the available data for comprehensive customer recovery. Expert G reveals that such organizations even have accurate data on where the customers have migrated as well as what their last transaction was. According to expert A, they can use this defined criteria to decide on customer recovery investments, like the time since the last transaction of the customer with the organization, to address the customers individually. Additionally, they regard lists that exclude customers that the organizations do not want to win back when deciding on customer recovery investments. With regard to expert C's organization, it uses customer data to exactly determine whether a customer still has an active relation with the organization. In the case of established, medium-sized organizations, like the organizations of experts E and F, the process customer recovery is not completely digitized and automatic, but it is customer-specific and personal. Expert E emphasizes that the smaller an organization, the lesser the likelihood of it being centrally managed. Thus, these organizations try to avoid customer migration by carrying out customer-specific offers with face-to-face contact for recovery. According to expert F, such organizations have a partially digital customer data base, which they can use to find information on the current customer status to identify the ones to invest in. There are several possibilities for investments in customer recovery. The expert interviews reveal that there are also differences in the channels that the different organizations choose for customer recovery. The established, medium-sized organizations and corporations, such as the organizations of experts E and F, use more traditional channels such as personal contact, print, letter, or email, while the newer fully digitized organizations make estimations using in-app push notifications, short message service (SMS), and instant messaging applications. Table 3.2-9 summarizes the major findings from the interviews regarding the current status of practice and lists the experts who support them.

Table 3.2-9 Major findings from the interviews regarding the current status of practice and list of experts who support them

Major findings from the interview	Supported by expert(s)…
Affirmation of the importance of managing customer recovery	A, B, C, D, E, F, G
Implementing customer recovery management in the organization	A, B, C, D, E, F, G
Decentrally managed customer recovery	B, D
Fully digitized customer recovery by using customer data	A, C, G
Not completely digitized and automatic, but customer-specific and personal customer recovery	E, F
Use of traditional channels such as personal contact, print, letter, or email for customer recovery	E, F
Use of newer and digitized channels such as in-app push notifications, short message service (SMS), and instant messaging applications	A, C, G

In conclusion, no organization uses a quantitative decision for investments in customer recovery. Most of the organizations do not even consider a customer's profitability and often keep customer recovery very simple (expert A, B, C, E and F). Only a few make their decisions on the basis of statistical estimates and an economic calculus (expert D and G). Nevertheless, it is essential for organizations, especially the fully digitized ones, to use a decision model with a well-defined logic to make automated decisions on customer recovery. To build the organizations a foundation for their decisions, in the following, we propose a decision model to decide on customer recovery investments.

Expert Interviews on Applicability

Expert B confirms the good comprehensibility of the decision model. Moreover, experts D and G emphasize that the decision model is profound and the focus on the "dying" customers is important as customer recovery management gets increasingly critical in the digital world. Expert E also supports distinguishing customers as "alive," "dying," and "dead" by emphasizing the meaningfulness of the customer status "dead." The reason for this is that every organization has customers that they do not want to make active again due to them running to the court or dunning procedures, for instance. Consequently, it is indispensable to consider these customers when deciding about customer recovery investments. However, according to expert E, organizations should be aware of the fact that investing in customer recovery also raises the risk of annoying customers, and thus, possibly reducing customer satisfaction. Expert A makes a similar comment, in that, he mentions that investing in customers who are “alive” is a wrong decision as it is very important for the organization to provide existing customers with the same actions and benefits as inactive customers who can be recovered. As such, they anticipate a decreasing likelihood of customers who are “alive” migrating.

Apart from that, to make investment decisions the organizations have to collect the necessary data, namely the probability of the customer relation “dying” $P_i("dying"|Information)$, present value of future cash inflows of a customer relation π_i, the investment costs I_j, and the effectiveness factor η_{ij}. Hence, we asked the experts if this necessary data is available in their organizations. All of the interviewed experts state that $P_i("dying"|Information)$ is available due to digitized customer data. However, some of the experts mention that such a customer database is presently missing in their organizations (expert B, E, and G). While experts B and G emphasize that their organizations are working on the roll-out of an integrated CRM system at the moment, expert E points out that for medium-sized organizations the effort would be disproportionally high, which is the reason they do not implement such a database. The personal contact between the customers and the organizations is pronounced, which is why the decisions on customer recovery have not been made digitally and automatically. As regards the present value of future cash inflows of a customer relation π_i the interviews have indicated that the organizations here have different approaches. In contrast, expert D’s organization would use the CLV for calculations, expert G explains that they would take the average turnover of a customer group as the basis for investment decision. Expert A would only calculate the model for the next period and for long-term. Hence, he would also calculate the present value of future cash inflows of a customer relation only for the subsequent period. The expert interviews indicated that no expert sees a problem in determining the investment costs I_j. Finally, experts D and G reveal that the effectiveness factor η_{ij} can be estimated according to an empirical value, a market research, or control groups. Only expert F indicates doubts regarding the effectiveness factor η_{ij} because the results of empirical values of the organization are very volatile.

In addition to the relevance of the decision-making model and the availability of the input parameters, many of the experts regard the decision model as good decision support for their organization. Expert C claims that the model is quite useful as an economic decision-making tool. In particular, as the organization has not yet made any investment decision for customer recovery according to an economic decision-making model and have only done so on intuition. Additionally, expert D points out that the method could complement the collaboration of the organizations' headquarters and the sales departments and agencies. Thus, the benefits from the information obtained in the decision-making model can be combined with the personal impression of the sales force. Moreover, Expert G appreciates the possibility of customer-specific consideration offered by the decision model. Such a customer-specific consideration is the future goal of his organization. So far, the customers are divided into customer groups to help in making recovery decisions. One reason for this is that, despite modern information and communication systems, the exact data of each single customer is not available to make decisions on a customer-specific basis. This is confirmed by expert C, who also points out that the customers are segmented for analysis measures. Nevertheless, the experts consider the model to be applicable in their organization, as a formal approach to a decision model enables the analysis of customer groups as well. Table 3.2-10 summarizes the major findings from the interviews regarding the applicability of the decision model and lists the experts who support them.

Table 3.2-10 Major findings from the interviews regarding the applicability of the decision model and list of experts who support them

Major findings from the interview	Supported by expert(s)…
Good comprehensibility of the decision model	B
Focus on "dying" customers is important for customer recovery	D, G
Importance of the differentiation between "alive," "dying," and "dead" customers	E
Easy ascertainment of $P_i("dying"\|Information)$	A, B, C, D, E, F, G
Easy ascertainment of the present value of future cash inflows π_i (using different approaches)	A, D, G
Easy ascertainment of the investment costs I_j.	A, B, C, D, E, F, G
Easy ascertainment of the effectiveness factor η_{ij}	A, B, C, D, E, G
Decision model is a good decision support for organizations	C, D, G

In summary, the expert interviews indicate that the decision model for customer recovery investments is meaningful, enriching, and is practically applicable. Nevertheless, it cannot be applied to all organizations in a generalized manner, as each organization has different requirements and different objectives. Although the decision model provides a profound basis for making decisions regarding customer recovery investments, each organization and business model must separately examine how the model is compatible with their prerequisites and objectives and the adjustments and assumptions required for its application.

3.2.5 Summary and discussion

In this paper, we point out that the distinction between "alive," "dying," and "dead" customer relations for is challenging for customer recovery because of increasing market transparency and impersonal nature. Hence, organizations risk wrong investment decisions when it comes to customer recovery. Addressing this challenge, the extant literature various discussions and models concerning investments in customer relations (Table 3.2-1). However, to the best of our knowledge, no approach considers the probabilities of a customer relation being “alive,” “dying,” and “dead” for such investment decisions. Therefore, we combine these ideas in a formal decision model to decide on customer recovery in an economically reasonable manner by considering these probabilities. In doing so, we strive for practical applicability and demonstrate the decision model’s operationalization in an illustrative example and discuss its applicability in interviews with experts from practical fields.

Nevertheless, our decision model has limitations that stimulate further research. First, further research should examine the decision model in a real world context to evaluate its usefulness more precisely (Sonnenberg & Vom Brocke, 2012). However, we can evaluate the decision model in terms of its applicability, completeness, understandability, feasibility, and operationality with an example. In doing so, we follow Sonnenberg and Vom Brocke (2012), and argue that it is reasonable to disseminate research findings at early stages to communicate them to interested peers and research communities. Second, the decision model is designed to cover a single period. In practice, to permanently ensure maximum of customer recovery, periodical assessments could be a possible extension of the decision model. Third, in the decision model it is assumed that the organization’s decision regarding customer recovery investments is risk neutral. In reality, risk attitude can be context and branch specific, which should be examined in future research. Finally, we assume that investing in a customer relation that is “alive” is not reasonable in terms of the recovery effect. In reality, recovery investments could also increase the satisfaction of customer relations that are “alive.”

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4 Part C: Behavior of individuals in a digital world

4.1 The disclosure of private data: Measuring the privacy paradox in digital services

Abstract

Privacy is a current topic in the context of digital services because such services demand mass volumes of consumer data. Although most consumers are aware of their personal privacy, they frequently do not behave rationally in terms of the risk-benefit trade-off. This phenomenon is known as the privacy paradox. It is a common limitation in research papers examining consumers' privacy intentions. Using a design science approach, we develop a metric that determines the extent of consumers' privacy paradox in digital services based on the theoretical construct of the privacy calculus. We demonstrate a practical application of the metric for mobile apps. With that, we contribute to validating respective research findings. Moreover, among others, consumers and companies can be prevented from unwanted consequences regarding data privacy issues and service marketplaces can provide privacy-customized suggestions.

Keywords: Privacy paradox, Privacy calculus, Metric, Digital services

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4.1.1 Introduction

In the information age, the significant quantity of available data enables organizations to create detailed descriptions of individuals (Hashem et al., 2015). Enabled by information and communication technologies (ICT), the resulting profiles can, for example, be used for personalized marketing campaigns or advertising (Egelman et al., 2013; Hauff et al., 2015). However, this usage is not always with the knowledge of consumers. Platform and service operators may be regarded as unreliable actors in part using data for unauthorized or unintended purposes (Alt et al., 2015). Invasion of privacy can result in serious negative effects, for example, legal consequences may arise if a person acts on behalf of others and, thus, abuses their identities. Financial implications may include financial losses caused by third parties hacking into a personal account (Hauff et al., 2015). Massive data access facilitates collecting, sharing, buying, or selling of private data, and entails storing, manipulating, mining, and analyzing these data (Malhotra et al., 2004). Currently, most consumers already have a pronounced perception toward privacy and pursue the goal of protecting themselves from their private data being misused (Egelman et al., 2013; Kumaraguru & Cranor, 2005). Especially, the third-party use of data is seen with particular care by customers (Spiekermann et al., 2001). Put together, the easy dissemination of data raises the awareness of privacy and makes privacy a current topic for information hubs such as electronic markets (Alt et al., 2015).

However, despite these risks, consumers are usually unable to estimate the amount and economic value of the personal data they provide (Buck et al., 2014). Consequently, consumers have a propensity to not protect themselves enough against privacy risks and disclose private data despite the associated imminent dangers (Acquisti, 2004). This phenomenon reveals the unrealistic assumption of individual rationality in the context of personal privacy. Despite making the statement that they want to protect their privacy, consumers act contrarily (Acquisti, 2004). This phenomenon is called the privacy paradox (Norberg et al., 2007).

The growth of digital services in ICT amplifies the challenges concerning privacy issues. In general, a service is defined as “any activity or benefit that one can offer to another that is essentially intangible” (Kotler & Armstrong, 2010, p. 248). A digital service is a service provided over electronic networks (Graupner et al., 2015). Consumers’ privacy is even more threatened because digital services such as mobile apps or social media have enormous demand for consumer data (Stutzman et al., 2013; Wei et al., 2012). For example, mobile apps can easily collect sensitive data, such as photos and files, contact lists, or location information, thus supporting the increase in data collection (Egelman et al., 2013; Wei et al., 2012; Zhou, 2013). Consequently, consumers in particular who use smartphones and, thus, mobile apps, are faced with a special challenge concerning their privacy (Horbach, 2013). Yet they continue to download, install, and use a significant number of apps. Current download rates and forecasts show a booming app economy (Buck et al., 2014). In addition, consumers hardly pay attention to or comprehend app permissions (Felt et al., 2012), even though technical capabilities enable the spreading and targeted usage of this mass of personal consumer information. Additional factors exist that reinforce the enormous usage of apps and lead to the collection of consumer information. For example, by integrating smartphones into their daily life (Abdelzaher et al., 2007; Buck et al., 2014) and trusting them, some consumers use mobile apps without a clue as to how they invade privacy (Horbach, 2013). Furthermore, consumers expect several benefits, such as social adjustment, time savings, and pleasure, or face social pressure to use apps (Hui et al., 2006; Smith et al., 2011). These factors also explain the booming app economy with apps as a special type of digital service (Buck et al., 2014; Hui et al., 2006; Krasnova & Veltri, 2010; Schreiner & Hess, 2015).

The vulnerability of consumers' privacy in the context of digital services results in the loss of control over personal information and unwanted data disclosure (Bélanger & Crossler, 2011; Dinev & Hart, 2006). Additionally, this vulnerability supports business models for digital service providers whose most important type of revenue is based on information (Buck et al., 2014). Thus, consumers gather the benefits of free digital services only in return for providing their personal data (Buck et al., 2014). Although the clueless handling of privacy is primarily a consumer problem, it also has implications for digital service providers because they compete for consumers (Culnan & Armstrong, 1999). Moreover, their economic success is determined by a strong reputation, which in turn depends on the responsible handling of consumers' privacy (Culnan & Armstrong, 1999; Degirmenci et al., 2013).

Consumer privacy is a well-known research subject. Topics such as the privacy calculus (Culnan & Armstrong, 1999; Min & Kim, 2015; Smith et al., 2011) and privacy concerns (Buchanan et al., 2007; Krasnova et al., 2009; van Slyke et al., 2006; Zukowski & Brown, 2007) are frequently mentioned in the literature. However, many researchers focus on examining factors that betray consumers and induce them or keep them from disclosing personal information (Son & Kim, 2008). They also focus on factors that affect an individual's privacy concerns, such as privacy experience, personality traits, or privacy awareness (Smith et al., 2011). In these cases, it is theoretically assumed that consumers behave rationally according to a risk-benefit calculation — the privacy calculus. The perceived risks of disclosing personal information are opposed to the perceived benefits expected from doing so (Chellappa & Sin, 2005; Dinev et al., 2006; Dinev & Hart, 2006; Xu et al., 2009). However, actual consumer behavior, which is affected by bounded rationality or missing information, is neglected. The so-called privacy paradox, which "represents a form of irrational, or bounded-rational decision making" (Keith et al., 2012, p. 3), is already discussed in extant literature. Yet, this literature only discusses and demonstrates that consumers do not keep to their stated privacy concerns. However, to the best of our knowledge, no research exists that has developed a metric to calculate the extent of the privacy paradox for either digital services or any other application domain. To overcome this research gap, we use a design science research approach following Peffers et al. (2007) to address the following objective in this paper.

Design objective: Development of a privacy paradox metric (PPM) as a design artifact that aggregates consumers' privacy intentions and behavior to a single measure and quantitatively assesses the extent of consumers' paradoxical privacy behavior in the context of digital services.

We focus on digital services because consumers' privacy is even more vulnerable in this context given that these services require a large volume of personal data. A metric is defined as a standard of measurement (Merriam Webster, 2017). Such a standard is a human created artifact and, as such, should be accurately designed. Prior research considers metrics as artifacts that are objects for design science research (Offermann et al., 2010). Being the first quantitative measure of the extent of the privacy paradox, the PPM will have several advantages for researches, consumers, the companies offering digital services, ICT platform providers, and consumer protection organizations. Research can use the metric to validate empirical results towards consumers' data privacy intentions, as the privacy paradox is a limitation in many data privacy research papers. To consumers, the PPM could provide transparency about an individual consumer's privacy paradox to save them from careless disclosure of data and thus unwanted consequences. Accordingly, also companies offering digital services can use the PPM to identify careless consumer decisions towards data disclosure and manage the risk related to such decisions. ICT service providers, such as app stores, can use the PPM to enhance their attractiveness by providing customized warnings, suggestions, sorting, or filtering. Consumer protection organizations can build further empirical studies on the PPM that increase public awareness on the risks related to the privacy paradox.

To achieve the design objective, we follow the design science research methodology (DSRM) (Hevner et al., 2004; Peffers et al., 2007) and contribute a design theory (Gregor, 2006; Gregor & Hevner, 2013; Gregor & Jones, 2007) to measure the extent of the privacy paradox. The structure of this paper is similar to the publication scheme suggested by Gregor and Hevner (2013). First, we present the theoretical background of the topic in Section 4.1.2. Next, we deduce the requirements that the metric must fulfil to guarantee high quality and to declare the basic notion and calculation of the privacy paradox metric in Section 4.1.3 and 4.1.4. Subsequently, we describe an exemplary application of the PPM and its results in Section 4.1.5. Afterwards, we evaluate the metric against the requirements in Section 4.1.6. Finally, we show the theoretical contribution, limitations, and managerial implications in the discussion and conclude in Section 4.1.7.

4.1.2 Theoretical background

Our research contributes to a stream of literature on data privacy in information systems (IS) and related fields. Thus, we review this research and build our metric on it.

A person's privacy has evolved into one of the most important ethical topics of the information age (Mason, 1986). The main reason for this development is that we live in an age of information overload (Zhan & Rajamani, 2008). The broad dissemination of information enables companies to collect significant quantities of information on their consumers in order to meet consumer demands and to remain competitive (Culnan & Armstrong, 1999; Nissenbaum, 1997; Zhan & Rajamani, 2008). Companies expect even greater advantages from promising consumer data, such as improving consumer retention, increasing revenue, having a better understanding of existing and prospective consumer needs, better recommendations or increasing productivity (Heimbach et al., 2015; Spiekermann et al., 2001; Tene & Polonetsky, 2012; Zhan & Rajamani, 2008). However, as companies collect an increasing amount of data, they tend to forget the fundamental right to privacy (Spiekermann et al., 2001). The same information, which brings significant advantages for companies, also results in increasing privacy concerns on the consumer side (Zhan & Rajamani, 2008), such as social, psychological, resource-related, independence-related, legal, and physical consequences (Hauff et al., 2015).

In a contemporary interpretation, privacy refers to an individual's control over sensitive information about oneself (Bélanger et al., 2002; Bélanger & Crossler, 2011; Stone et al., 1983). At the individual level, countless differences exist in the desire for privacy (Hawkey & Inkpen, 2006). Zukowski and Brown (2007) find that certain demographic factors, such as age, education, and income level, affect the privacy concerns of individuals, whereas factors such as gender or Internet experience have no influence. In contrast, Cho et al. (2009) show that gender and Internet experience apparently influence individuals' privacy concerns. Likewise, knowledge and own preferences affect the privacy attitude (Acquisti et al., 2015). Frequently, people cannot imagine that their data disclosure can have serious consequences for them. In addition to the missing knowledge, own preferences, emotions, and thoughts change in different situations and stages of life (Acquisti et al., 2015), which also affects information disclosure and privacy conditions. However, privacy is different not only on an individual level but also with respect to cultural- and context-related deviations (Acquisti et al., 2015).

Regarding privacy concerns, several individual differences exist (Acquisti & Grossklags, 2005). Every consumer makes decisions about his or her own privacy every day, such as when deciding to use or not use a digital service. A prevalent model for such decisions is the privacy calculus, which represents "the most useful framework for analyzing contemporary consumer privacy concerns" (Culnan & Bies, 2003, p. 326). In this way, it is possible to consider individual circumstances by weighing personal preferences for benefits and risks (Dinev & Hart, 2006; Laufer & Wolfe, 1977). Although risks reduce the individual's readiness to disclose private data, benefits have the reverse effect (Laufer & Wolfe, 1977). To make the calculus more illustrative, Hui et al. (2006) list two categories of potential benefits, namely extrinsic (monetary saving, time saving, self-enhancement, social adjustment) and intrinsic (pleasure, novelty, altruism) benefits. Roeber et al. (2015) find that most customers disclose their personal information if the benefits fulfil their needs. The greater the benefits of a digital service, the more the consumer is willing to disclose data to be able to use the service. Risks are understood as the possible intrusion of privacy within the risk of losing personal data to a company and the potential danger of the data being misused (Malhotra et al., 2004; Smith et al., 1996; Smith et al., 2011). Hence, risks are viewed as the result of two factors: the perceived likelihood of a potential privacy invasion and the perceived damage it causes (Cunningham, 1967). The higher risk of using a digital service results in a lower likelihood that the consumer will use the service.

Most researchers assume that people behave rationally when they decide about their privacy and that they weigh the benefits and risks (Acquisti & Grossklags, 2005). Also, the privacy calculus is based on this assumption (Keith et al., 2012). Nevertheless, an opposite behavior is observed and behavioral intentions to disclose information are not a precise predictor for actual behavior (Norberg et al., 2007). People who claim to have strong privacy concerns and no purpose for revealing their data give the information away despite that attitude. The term privacy paradox denotes such behaviour (Acquisti & Grossklags, 2004; Norberg et al., 2007). Researchers show that people behave contrarily to their reported privacy attitudes and concerns (Bélanger & Crossler, 2011; Norberg et al., 2007; Smith et al., 2011). Thus, in many cases, the stated privacy concerns do not correspond to their real behavior and consumers act boundedly rational or irrationally (Acquisti & Grossklags, 2004).

Prior literature repeatedly verifies this behavior. Spiekermann et al. (2001) show that consumers disclose private data to online shops despite having privacy concerns. They conduct an experiment to measure the self-reported privacy attitudes and compare them with their actual disclosing behavior in an online shopping environment. They confirm that most consumers do not keep to their stated privacy preferences. Additionally, Norberg et al. (2007) investigate a study to determine whether or not people live up to their reported intentions toward privacy. Thereby, they reinforce the existence of the privacy paradox because they find that consumers provide substantially more private data than they profess. Additional examples exist for the examination of the privacy paradox in e-commerce scenarios, such as from Jensen et al. (2005) and Berendt et al. (2005). The privacy paradox cannot be demonstrated only in the online shopping and marketing context but also through social media. Acquisti and Gross (2006) point out that privacy concerned persons are members of Facebook and disclose a large amount of private data, thus behaving paradoxically.

4.1.3 Development of the privacy paradox metric

A metric is a mathematical model that is able to measure aspects of systems, system designs, or behavior in the interaction with systems (Offermann et al., 2010). In general, measuring means assigning a number to an object to express some aspect of it in a quantitative manner. Any form of measurement is an abstraction that reduces the complexity of the object's attributes to a single number (Böhme & Freiling, 2008). In this way, a metric provides measures that managers understand and that academics can replicate and analyse (Palmer, 2002). In addition, practitioners and researchers use metrics to make better decisions (Hauser & Katz, 1998).

To ensure a high quality for the PPM, we first present the requirements that the metric must fulfill. Subsequently, we introduce the metric's basic concept and its calculation. Using a metric as a suitable artifact for design science research (Offermann et al., 2010), we meet the design science guideline that suggests that "design science research must produce a viable artifact" (Hevner et al., 2004, p. 83).

Requirements for the privacy paradox metric

Metrics are specifically used to evaluate certain decision alternatives (Kaiser et al., 2007; Linkov et al., 2011). Because their requirements are context-dependent, they cannot be used to evaluate metrics in general. Moreover, no metric exists to measure the privacy paradox and, thus, no set of appropriate requirements exists to reference. Consequently, we deduce requirements from research on the development of a metric, on measurement instruments, and on requirements for data quality metrics, security metrics, and software quality metrics (Becker et al., 2015; Liggesmeyer, 2009; Wallmüller, 2001). As a result, we compile the following list of seven requirements, present definitions, and show the related requirements used in research (see Table 4.1-1).

Table 4.1-1 Requirements for the PPM

Requirement		Related requirements
Quantifiability	"The unit of measure is clearly set, absolute, and appropriate so that the metric can be based on quantitative measurements." (Erl et al., 2013, p. 405)	*Quantification* (Böhme & Freiling, 2008; Kaiser et al., 2007)
Precision	"The degree of mutual agreement among individual measurements made under prescribed conditions […]. Precision captures the notion of the repeatability of accurate measurements under similar conditions." (Herrmann, 2007, p. 29)	*Repeatability* (Erl et al., 2013; Liggesmeyer, 2009), *Reliability* (Wallmüller, 2001)
Comparability	"The units of measure used by a metric need to be standardized and comparable." (Erl et al., 2013, p. 405)	*Analyzability* (Liggesmeyer, 2009) *Normalization* (Kaiser et al., 2007)
Obtainability	"The metric needs to be based on a non-proprietary, common form of measurement that can be easily obtained and understood by […] consumers." (Erl et al., 2013, p. 405)	*Feasibility* (Kaiser et al., 2007) *Reliability* (Böhme & Freiling, 2008)
Interpretability	"The actual measure should be easy to interpret by business users." (Even & Shankaranarayanan, 2007, p. 83)	*Simplicity* (Liggesmeyer, 2009)
Usefulness	"A metric is considered useful if the metric corresponds to the intuition of the measurer [and] is actively used in a	

	decision making process.” (Bouwers et al., 2013, p. 2)	
Economy	“From an economic view, only those measures must be taken that are efficient with regard to costs and benefit.” (Kaiser et al., 2007, p. 2)	

In addition to the requirements listed in Table 4.1-1, accuracy (Herrmann, 2007) is an important requirement for evaluating the metric because accuracy is defined as “the degree of agreement of individual or average measurements with an accepted reference value or level” (Herrmann, 2007, p. 29). However, as there is no reference value for the measurement of the privacy paradox so far, it is not possible to apply this evaluation criterion for the PPM.

4.1.4 Basic concept and calculation

Using the requirements previously identified, we develop the PPM. To establish the PPM, we use the concept of the privacy calculus, which is useful to explain consumers’ intention to disclose any information (Keith et al., 2014). According to the privacy calculus, consumers weigh the perceived risks of a decision that may involve a privacy threat against the perceived benefits that result from the information disclosure (Dinev & Hart, 2006; Laufer & Wolfe, 1977; Sheng et al., 2008). Consequently, consumers accept a loss of their privacy as long as the benefits outweigh the imminent risks (Sheng et al., 2008). Moreover, the theory of reasoned action (TRA) implies that actual behavior matches the intention to disclose information (Fishbein & Ajzen, 1975). However, consumers do not always act rationally according to their privacy calculus (Acquisti & Grossklags, 2004; Norberg et al., 2007). Consequently, a contradiction exists between consumers’ privacy intentions and behaviors (Keith et al., 2012; Keith et al., 2013; Norberg et al., 2007). This phenomenon is called the privacy paradox (Bélanger & Crossler, 2011; Smith et al., 2011) and can be identified if consumers use a digital service, although their intentions imply not using it (and vice versa). However, the case for using a service paradoxically constitutes the privacy relevant part because it involves a violation of consumers' privacy, whereas a paradoxical non-usage only implies a loss of utility for consumers. Figure 4.1-1 depicts this difference between intention and actual behavior in the form of rational and paradoxical service usage and non-usage. Consumers are classified in one of the four segments according to their modeled privacy calculus. This classification shows consumers’ privacy intention with respect to the information disclosure. Because the perceived benefit and the perceived risk are not measured on directly comparable scales, the classification in the four segments is necessary. Depending on the consumer's classification, whether the consumer behaves rationally or paradoxically can be determined.

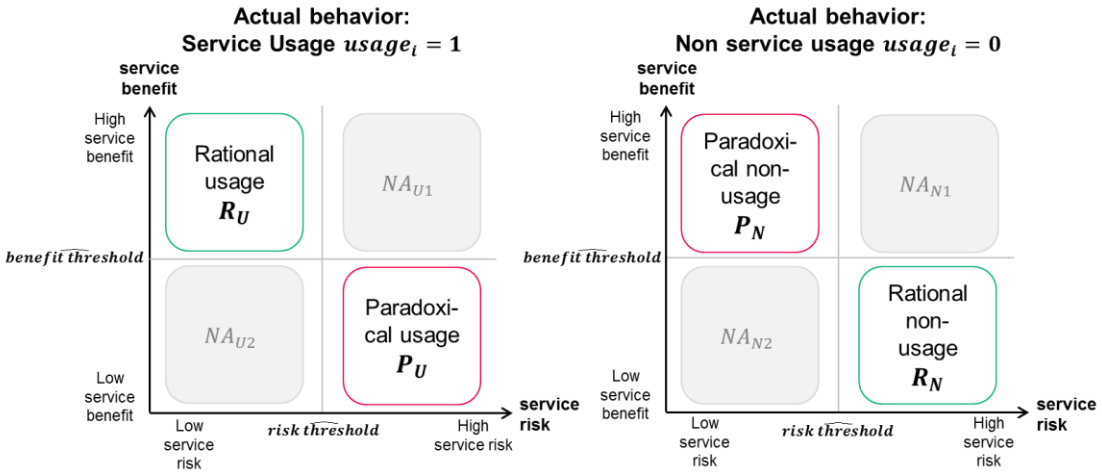

Figure 4.1-1 Illustration of rational and paradoxical consumer privacy behavior

Figure 4.1-1 shows the two different types of paradoxical and rational behavior. The top left of the figure indicates low perceived risk and high perceived benefit. Consequently, a service usage seems rational (R_U), whereas a non-service usage is paradoxical (P_N). In contrast, the segment in the bottom right is characterized with a high perceived risk and a low perceived benefit. Thus, P_U represents consumers using a service, even if they recognize only a relatively small benefit and perceive the risk as relatively high. All consumers, which are classified in the segment R_N, use the digital service rationally. However, in some segments, the *PPM* is not applicable because no clear conclusions can be made about the rational respectively paradoxical behavior, marked by NA_{U1}, NA_{U2}, NA_{N1}, and NA_{N2}. In such cases, the weighing up between the consumer's service benefit and attitude toward the service's risk do not result in incontestable conclusions.

The *PPM* determines the percentage of consumers who behave paradoxically according to the modeled privacy calculus. Therefore, we first model the $service\ benefit_i$ and the $service\ risk_i$ for consumers i ($i = 1, \ldots, n$).

$service\ benefit_i \in [service\ benefit_{min}, service\ benefit_{max}] \forall i, service\ benefit_{min} < service\ benefit_{max}$ is composed of several dimensions (see Formula 1).

$$service\ benefit_i = \sum_{j=1}^{m} benefit\ weight_{ij} * service\ benefit\ dimension_{ij} \quad (1)$$

These benefit dimensions can, for example, be taken from technology acceptance models, such as hedonic motivation or perceived usefulness, because these models define constructs that predict the behavioral intention to use a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). The constructs j $(j = 1, \dots, m)$ affecting the consumer's $service\ benefit_i$ are service and context dependent (Venkatesh et al., 2012). Each consumer can rate the single constructs j with a personal assessment $service\ benefit\ dimension_{ij} \in [service\ benefit_{min}, service\ benefit_{max}] \forall i, j$. To create differences in the importance of the chosen constructs, they are weighted with the construct and consumer-specific factor $benefit\ weight_{ij} \in [0,1]$ with $\sum_{j=1}^{m} benefit\ weight_{ij} = 1\ \forall i$.

A digital service may be required to use many different types of information, such as identity, credit card information, and location (Lioudakis et al., 2007). Consequently, consumers' $service\ risk_i \in [service\ risk_{min}, service\ risk_{max}] \forall i, service\ risk_{min} < service\ risk_{max}$ is also service and context dependent. The service can demand k $(k = 1, \dots, p)$ different permissions that are assessed for each consumer i with an permission dependent valuation $permission \in [service\ risk_{min}, service\ risk_{max}] \forall i, k$, and that can be weighted using the permission specific factor $risk\ weight_{ik} \in [0,1]\ with\ \sum_{j=1}^{p} risk\ weight_{ik} = 1$.

$$service\ risk_i = \sum_{k=1}^{p} risk\ weight_{ik} * permission_{ik} \quad (2)$$

Given the paradox, which states that intention to disclose private data is not necessarily a predictor of actual use, we need information on whether a consumer actually uses the service. Therefore, we introduce usage $usage_i = \begin{cases} 0, & for\ non-usage \\ 1, & for\ usage \end{cases}$.

To distinguish among the four segments illustrated in Figure 4.1-1 that stand for the different intentions to disclose private data, x- and y-axes $\widehat{benefit\ threshold}$ and $\widehat{risk\ threshold}$ are required. Therefore, we denote $Benefit$ as the distribution of consumers' $service\ benefit_i$. f is a function that maps distribution $Benefit$ to a scalar $\widehat{benefit\ threshold}$ on the interval $[service\ benefit_{min}, service\ benefit_{max}]$. f could, for example, be the mean or any quantile such as the median. The same analogously applies for $\widehat{risk\ threshold}$.

$$\widehat{benefit\ threshold} = f(Benefit) \tag{3}$$

$$\widehat{risk\ threshold} = f(Risk) \tag{4}$$

Finally, we determine the rational (R_U and R_N) and paradoxical (P_U and P_N) behavior, as well as the NA_U and NA_N, using the $classification_i$ (see Formula 5). This classification relates the actual behavior of the consumer i to his or her perceived benefit and risk of the service. Formula 5 represents the same classification that is graphically displayed as matrices in Figure 4.1-1. As an example for this classification, a consumer, who uses a digital service and has a higher $service\ benefit_i$ than the $\widehat{benefit\ threshold}$ and a lower attitude towards the $service\ risk_i$ than the $\widehat{risk\ threshold}$, is segmented into R_U, which represents a rational service usage. The reason for this is that the consumer appreciates the benefit of a digital service more than the risk.

$$a_i = \begin{cases} R_U, & usage_i = 1 \wedge service\ benefit_i > \widehat{benefit\ threshold} \wedge service\ risk_i \leq \widehat{risk\ threshold} \\ P_U, & usage_i = 1 \wedge service\ benefit_i \leq \widehat{benefit\ threshold} \wedge service\ risk_i > \widehat{risk\ threshold} \\ NA_{U1}, & usage_i = 1 \wedge service\ benefit_i > \widehat{benefit\ threshold} \wedge service\ risk_i > \widehat{risk\ threshold} \\ NA_{U2}, & usage_i = 1 \wedge service\ benefit_i \leq \widehat{benefit\ threshold} \wedge service\ risk_i \leq \widehat{risk\ threshold} \\ P_N, & usage_i = 0 \wedge service\ benefit_i > \widehat{benefit\ threshold} \wedge service\ risk_i \leq \widehat{risk\ threshold} \\ R_N, & usage_i = 0 \wedge service\ benefit_i \leq \widehat{benefit\ threshold} \wedge service\ risk_i > \widehat{risk\ threshold} \\ NA_{N1}, & usage_i = 0 \wedge service\ benefit_i > \widehat{benefit\ threshold} \wedge service\ risk_i > \widehat{risk\ threshold} \\ NA_{N2}, & usage_i = 0 \wedge service\ benefit_i \leq \widehat{benefit\ threshold} \wedge service\ risk_i \leq \widehat{risk\ threshold} \end{cases} \tag{5}$$

We depict the detailed subdivision in the segments for a better understanding of the basic idea of the *PPM*, although the segments R_U, NA_{U1}, NA_{U2}, R_N, NA_{N1}, and NA_{N2} are not fundamentally necessary to calculate the *PPM*. Because different types of *R*, *P*, and *NA* exist for service usage and non-usage, two calculation bases also exist for the *PPM*. $PPM_U \in [0,1]$ represents the percentage of service users behaving paradoxically (see Formula 6), or the percentage of consumers using a service, although such actual behavior is not rational. This phenomenon results in unwarranted data disclosure on the consumer's side and, thus, represents the more important metric regarding privacy. $\widetilde{P_U}$, $\widetilde{R_U}$, and $\widetilde{NA_U}$ represent the number of elements of the $classification_i$ with the attribute P_U, R_U, or NA_U, respectively.

$$PPM_U = \frac{\widetilde{P_U}}{\widetilde{P_U} + \widetilde{R_U} + \widetilde{NA_{U1}} + \widetilde{NA_{U2}}} \tag{6}$$

$PPM_N \in [0,1]$ represents the percentage of non-service users behaving paradoxically (see Formula 7). This metric shows the other side of paradoxical behavior, meaning the percentage of consumers who do not use a service even though they should according to the privacy calculus. $\widetilde{P_N}$, $\widetilde{R_N}$, and $\widetilde{NA_N}$ represent the number of elements of the $classification_i$ with the attribute P_N, R_N, or NA_N, respectively.

$$PPM_N = \frac{\widetilde{P_N}}{\widetilde{P_N} + \widetilde{R_N} + \widetilde{NA_{N1}} + \widetilde{NA_{N2}}} \tag{7}$$

PPM_U and PPM_N can both be integrated into a single number as well. $PPM \in [0,1]$ describes the share of all consumers who behave paradoxically (see Formula 8). $\alpha \in [0,1]$ is a weighting factor for PPM_U and PPM_N, which allows giving more weight to either paradoxical usage or non-usage in the calculation of the PPM. Thus, at the extreme, $\alpha = 1$ represents PPM_U, whereas $\alpha = 0$ signifies that only PPM_N is regarded.

$$PPM = \frac{\alpha\widetilde{P_U} + (1-\alpha)\widetilde{P_N}}{\alpha\left(\widetilde{P_U} + \widetilde{R_U} + \widetilde{NA_{U1}} + \widetilde{NA_{U2}}\right) + (1-\alpha)\left(\widetilde{P_N} + \widetilde{R_N} + \widetilde{NA_{N1}} + \widetilde{NA_{N2}}\right)} \tag{8}$$

In summary, the *PPM* represents the privacy paradox metric. It models individual consumers' privacy calculus, classifies their service usage or non-service usage as rational or paradoxical, and aggregates multiple consumers' intentions and behavior to a single measure. Thereby, higher values of the *PPM* indicate more paradoxical behavior.

4.1.5 Practical application of the privacy paradox metric

Mobile apps are a special type of digital service that we use to illustrate the application of the *PPM*. Consumers' intention to use a service can be determined by querying them on the service's perceived benefits and risk. The usage or non-usage of the service and, with that, the disclosure of private data enable conclusions about real behavior. The application context of mobile apps is particularly suitable for determining the *PPM* because the installation of a specific app is an indicator of consumers' willingness or lack thereof to release their data. App permissions, which provide access to private data on a smartphone (Egelman et al., 2013), need to be approved by consumers in the app store when installing the app (Keith et al., 2013). Thus, consumers can typically avoid the privacy invasion only by not installing the app (Egelman et al., 2013). With that knowledge, it is possible to draw conclusions about the gap between consumers' intention to disclose private data and their real behavior. Because perceived benefits and perceived risk are not readily available, consumers need to be asked for these measures in a survey. In August 2015, we conducted a survey with 715 participants from the 150 largest universities in Germany. In the following section, we first present a concrete ascertainment of the variables necessary for the *PPM* in the context of mobile apps. Subsequently, the results of the survey and the *PPM* are presented.

4.1.5.1 Determination of the privacy paradox metric in mobile apps

The survey questionnaire consists of four parts: app benefit and installation, app risk, and demographic data. The full German questionnaire is available from the authors upon request. The determination of the *PPM* in mobile apps abides by the formulas in Section 4.1.4. Before we discuss the operationalization of the PPM constructs in the context of mobile apps, we define requirements on the app selection process.

For this practical application of the *PPM*, the aim is to survey app users on their perceived benefits and risks associated with apps and compare this perception with actual installation behavior. To gain comparability across participants and limit the length of the questionnaire, we focus on five app categories. Further, to limit length of the questionnaire, we decided to not query benefits on the app level but the app category level. This requires app categories in which the benefits of different apps can reasonably be assumed rather homogenous and replaceable. Thus, we avoid app categories subject to network effects, such as present for online social networks or communication apps, for example, as this would violate the homogeneity assumption. Additionally, the consumers' usage decision depends on the monetary costs of an app. To keep the survey simple and to preserve the homogeneity of the apps, we consider only free apps and, thus only app categories where these are common. To ensure some degree of representativeness of the app category selection, we recruited 20 test subjects and analyzed their installed apps. As a result, the following five app categories are selected for the survey: navigation, note, radio, picture editor, and running. The questionnaire contains about ten popular examples for each app category and the option to enter additional apps.

To determine the consumer's $service\ benefit_i$ in a non-organizational context, we use $m = 2$ constructs of the extended unified theory of acceptance and use of technology (UTAUT2), namely, *hedonic motivation* and *performance expectancy*. "Hedonic motivation is defined as the fun or pleasure derived from using a technology" (Venkatesh et al., 2012, p. 161). It plays an important role and is a clear predictor of the intention to use it (Venkatesh et al., 2012). "Performance expectancy is defined as the degree to which using a technology will provide benefits to consumers in performing in certain activities" (Venkatesh et al., 2012, p. 159). Prior research found that performance expectancy is the main driver for the intention to use a technology (Venkatesh et al., 2012). In summary, both constructs are important drivers in explaining the intentions of consumers (Venkatesh et al., 2012). We operationalize hedonic motivation and performance expectancy with survey items adapted from the UTAUT2

(Venkatesh et al., 2012). Table 4.1-2 lists how items of the UTAUT2 are adjusted to measure the $service\ benefit_i$ for each consumer i. Similar to the UTAUT2, all items are measured using a seven-point Likert scale, with anchors being 1 ("strongly disagree") and 7 ("strongly agree").

Table 4.1-2 Example for determining the benefit of a service using survey items (Venkatesh et al., 2012)

Hedonic Motivation	**Performance Expectancy**
Using mobile apps is fun.	I find mobile apps useful in my daily life.
Using mobile apps is enjoyable.	Using mobile apps helps me accomplish things more quickly.
Using mobile apps is very entertaining.	Using mobile apps increases my productivity.

We capture the hedonic motivation and performance expectancy items of the UTAUT2 to detect consumers' $service\ benefit_i$ for each of the five app categories. Each participant was asked each question for each of the five app categories. We query a consumer's $service\ benefit_i$ at the level of app categories and not for single app, due to the practical reason that the complexity and length of the survey would arise otherwise. To assure equivalence between the questionnaire in German and the original English version, we conduct a standard translation and back-translation procedure (Brislin, 1970). To operationalize the two constructs and consumers' $service\ benefit_i$, we use the average of the 7-point Likert scale of the three questions for each construct. Thus, the minimum app benefit value $service\ benefit_{min} = 1$ and the maximum value $service\ benefit_{max} = 7$. For reasons of simplicity, we use equal weights for both benefits for all participants. Although the basic idea of the model enables differing weights as well. The weights can vary, as they can be different depending on whether they are utilitarian or hedonic apps and on what users expect from them. For example, some respondents give some of the apps more hedonic values or greater usefulness than others do. Formula 1 can be adapted to our survey context as follows:

$$service\ benefit_i = \frac{1}{2} * servic\ benefit\ dimension_{i1} + \frac{1}{2} * service\ benefit\ dimension_{i2} \quad (9)$$

To calculate the privacy paradox, we also need consumers' attitude toward the $service\ risk_i$. Therefore, it is necessary to identify the types of private data that consumers must disclose when they want to use the service. The questionnaire queried which apps a respondent has installed (yes/no question for about ten popular examples for each app category, option to list further installed apps). For each of these apps, the Google Play Store publicly provides the information on the permissions the respective app requests. Thus, for each of the five app categories under investigation, we know which apps an individual respondent has installed and which permissions each of these apps requests. Every claimed permission k must be asked about in the survey to determine the respective consumers' privacy concerns. Table 4.1-3 presents the corresponding permissions for the mobile app context ($p = 12$). The permission groups listed in the Google Play Store are taken as a basis for ascertaining the claimed permissions of the mobile apps. We have used the permissions of the apps to determine the risk, as the question whether a particular app has been installed can accurately and unambiguously determine whether the consumer is taking the risk or not. With other scales for privacy concerns (e.g., based on self-reported perceived risk), the risk would not be that clearly observable, and the data for the determination of the *PPM* would be diluted with the statements of consumers who are subject to paradoxical behavior. Analyzing the permissions requested by apps that the participant really installed anchors the calculation in observed behavior, not reported perception.

Table 4.1-3 Example for determining the risk of a service based on survey items

I think it is critical when mobile apps access my …	
Device and app history (Read sensitive log data, retrieve system internal state, retrieve running apps)	*Phone* (Directly call phone numbers, write call log, read call log, reroute outgoing calls)
Identity (Find accounts on the device, add or remove accounts)	*Photos/Media/Files* (Read the contents of your USB storage, modify or delete the contents of your USB storage)
Contacts (read and modify your contacts)	*Wi-Fi connection information* (view Wi-Fi connections)
Calendar (Read calendar events plus confidential information, add or modify calendar events, and send email to guests without owners' knowledge)	*Location* (Approximate location (network-based), precise location (GPS and network-based), access extra location provider commands)
Microphone	*Camera*

(record audio)	(Take pictures and videos)
SMS (Receive text messages, send text messages)	*Device ID and call information* (read phone status and identity)

Given the seven-point Likert scale, $service\ risk_{min}$ is 1 and $service\ risk_{max}$ is 7. We also use equal weights for all permissions for all participants for reasons of simplicity in this exemplary application, although permitting the collection of certain information can carry more weight in influencing one's use decision than others. To determine the risk of an app, only the permissions requested by the app and not required for the function of the app are considered. With that, we ensure that apps, which request more app permissions than others, are considered as more critical. This is implemented in the following calculation by considering app permissions that are not required with the value 0.

$$service\ risk_i = \sum_{k=1}^{12} \frac{1}{12} * permission_{ik} \qquad (10)$$

Further, to make the result comparable $service\ risk_i$ is scaled to the domain between 1 and 7.

To determine consumers' real behavior, the consumer's service usage $usage_i$ needs to be collected through questions on the mobile apps that each consumer i installed. Thus, the formula of the usage can be detailed $usage_i = \begin{cases} 0, & for\ no\ app\ installation \\ 1, & for\ app\ installation \end{cases}$.

Subsequently, we calculate the $\widehat{benefit\ threshold}$ and $\widehat{risk\ threshold}$. We use the median to transform distributions $Benefit$ and $Risk$ to scalars $\widehat{benefit\ threshold}$ and $\widehat{risk\ threshold}$. In doing so, we separate the higher half from the lower half of the data and divide the survey results into two parts of approximatively the same size. For the app category navigation, the outcome of our survey results are, for example, $\widehat{benefit\ threshold} = 4.17$ and $\widehat{risk\ threshold} = 3.75$.

By knowing all input parameters and the $classification_i$, it is possible to categorize consumers into different types of paradoxical (P_U and P_N) and rational (R_U and R_N) behavior on the one side and the NAs on the other side. Finally, we can calculate PPM_U, PPM_N, and PPM. In our practical application, we use $\alpha = 0.5$ as a weighting factor as we consider both PPM_U and PPM_N equally.

4.1.5.2 Results of the survey on mobile apps

4.1.5.2.1. Characterization of the sample

By distributing the questionnaire to students and university employees at the 150 largest universities in Germany, we were able to recruit 715 participants. Because our participants are on average 24 years old (ranging from 18 to 65 of age), we cannot claim that the results are representative of the entire population. However, the point is not to obtain representative measures of the *PPM* but to demonstrate the application of the metric. Our population is highly educated (57% higher education entrance qualification, 26% bachelor's degree, 8% master’s degree, 9% other) and is predominantly female (60%). Most of the participants (60%) are familiar with a smartphone and has used one for two years or longer. Out of these, 23% used smartphones for longer than five years. The frequency of new app installations is distributed in descending order: 45% of participants install less than one new app a month, 31% install one app a month, and 24% install more apps a month. Only 8% of participants have no navigation app installed and 63% have no radio app. The maximum average number of installed apps within the app categories is 1.12 for navigation, and the minimum is 0.48 for radio apps. With that the app categories navigation and radio represent the two extremes of most and least apps within an app category.

4.1.5.2.2. Assessment of app benefit

Table 4.1-4 shows the mean benefit values and the standard deviation for the five app categories distinguished between the two factors and in total. However, we calculate factor scores as the arithmetic mean of responses to assure comparability across the app categories. Based on the mean values of performance expectancy and hedonic motivation, the five app categories can be divided in three groups: predominant performance apps (navigation and note), predominant hedonic apps (radio and picture editing), and balanced apps (running).

Table 4.1-4 Results of the EFA for the app benefits of the app categories

App category	Performance expectancy		Hedonic motivation		Total	
	Mean	SD	Mean	SD	Mean	SD
Navigation	5.17	1.31	3.13	1.42	4.15	1.10
Note	4.13	1.77	2.59	2.59	3.36	1.42
Radio	2.40	1.42	3.47	1.95	2.93	1.57
Picture editing	2.78	1.63	3.92	1.99	3.35	1.65
Running	2.98	1.88	2.90	1.85	2.94	1.78

4.1.5.2.3. Assessment of app risk

In our survey, we asked all 715 respondents about their attitude toward app permissions (see Table 4.1-3). Thus, we can draw conclusions about their risk ranking subject to their risk on a scale from 1 (lowest) to 7 (highest). Data shows that respondents perceive the app permissions *Phone* (mean= 6.13, SD= 1.34), *Contacts* (mean= 6.07, SD= 1.39), and *Identity* (mean= 6.02, SD= 1.37) as being particularly critical, while *Location* (mean= 5.36, SD= 1.76), *Device and app history* (mean= 5.32, SD= 1.70), and *Wi-Fi connection information* (mean= 4.93, SD= 1.88) are the least critical.

Table 4.1-5 shows the mean, standard deviation, as well as the minimum and maximum value of $service\ risk_i$ by app category, which consider the permissions required by an app (see Formula 10). This result illustrates that navigation has the highest mean value regarding both risk and benefit. Further uni-dimensional results of the app benefit as well as the app risk can be found in Appendix 4.1.B.

Table 4.1-5 Distribution characteristics of app risk by app category

App category	Minimum	Mean	Maximum	SD
Navigation	1.14	3.66	5.48	0.95
Note	1.14	2.34	4.98	0.84
Radio	1.00	2.50	3.96	0.69
Picture editing	1.00	2.35	4.98	1.11
Running	1.00	3.18	5.48	1.10

4.1.5.2.4. Results of the privacy paradox metric in mobile apps

Although consumers not using a beneficial service only miss the added value, the usage of critical services is privacy relevant $(\widetilde{P_U})$ because private data are disclosed. Consequently, we focus on the more privacy important case of service usage $(usage_i = 1)$ in the following section. Using the surveyed data, we can instantiate the metric presented in Section 4.1.4 Figure 4.1-2 presents an exemplary distribution of consumers for navigation apps in the case of service usage $(usage_i = 1)$.

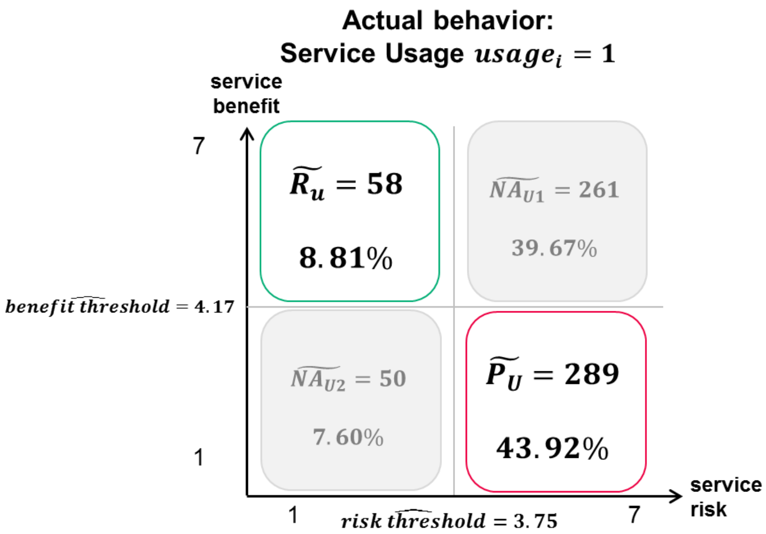

Figure 4.1-2 Distribution of participants (n=658) in segments for navigation apps in the case of service usage ($usage_i$=1)

These values represent the basis for the calculation of the *PPM* in the case of service usage (PPM_U). For instance, the PPM_U for navigation apps can be calculated as presented in Formula 11:

$$PPM_U = \frac{\widetilde{P_U}}{\widetilde{P_U} + \widetilde{R_U} + \widetilde{NA_{U1}} + \widetilde{NA_{U2}}} = \frac{289}{289 + 58 + 261 + 50} = 43.92\% \qquad (11)$$

The analogous results of PPM_U for all app categories are shown in Figure 4.1-3. Thereby, n represents the subsample of participants who have installed an app of the respective app category.

$\boldsymbol{Navigation}$ $(n = 658)$

$\widehat{benefit\,threshold} = 4.17$	$\widehat{risk\,threshold} = 3.75$	
	8.81%	39.67%
	7.60%	**43.92%**

$\boldsymbol{Note}$ $(n = 508)$

$\widehat{benefit\,threshold} = 3.50$	$\widehat{risk\,threshold} = 2.01$	
	12.01%	38.98%
	10.43%	**38.58%**

$\boldsymbol{Radio}$ $(n = 267)$

$\widehat{benefit\,threshold} = 3.00$	$\widehat{risk\,threshold} = 2.30$	
	25.47%	44.19%
	11.61%	**18.73%**

$\boldsymbol{Picture\ editing}$ $(n = 332)$

$\widehat{benefit\,threshold} = 3.50$	$\widehat{risk\,threshold} = 2.16$	
	31.63%	37.65%
	16.56%	**14.16%**

$\boldsymbol{Running}$ $(n = 303)$

$\widehat{benefit\,threshold} = 2.83$	$\widehat{risk\,threshold} = 3.17$	
	26.73%	56.44%
	5.28%	**11.55%**

Figure 4.1-3 Distribution of participants in segments and results of PPM$_U$ for all app categories

Table 4.1-6 additionally shows the results of the PPM in the case of non-service usage, PPM_N, and the integrated metric PPM for $\alpha = 0.5$, i.e., an equal weighting of service usage and non-usage.

Table 4.1-6 Results of PPM$_U$, PPM$_N$, and PPM for all app categories

App category	$\boldsymbol{PPM_U}$	$\boldsymbol{PPM_N}$	$\boldsymbol{PPM}$
Navigation	43.92%	38.84%	43.36%
Note	38.58%	31.40%	36.50%
Radio	18.73%	32.81%	27.55%
Picture editing	14.16%	29.24%	22.24%
Running	11.55%	24.27%	18.88%

As is seen in Figure 4.1-3, in this example the sum of $\widetilde{NA_{U1}}$ and $\widetilde{NA_{U2}}$ has a similar magnitude across all app categories. In contrast, the gap between rational and paradoxical behavior shows significant differences. Consumers using the radio and picture editing apps (hedonic apps) have a relatively weak PPM_U compared with the navigation and note apps (performance apps). That is, many consumers use an app even though they perceive a minor benefit and significant risk. This insight can be relevant for different interest groups, such as app providers, app stores, consumer protection organizations, and app users. App providers can use the results of the PPM_U to prevent serious consequences such as image damage or consumer migration. These consequences can arise when privacy concerned consumers become aware of their paradoxical privacy behavior because of incidents, such as leaked data misuse. App stores might use privacy as a competitive factor by applying the PPM_U to create consumer awareness for their paradoxical behavior. Consumer protection organizations can apply the PPM_U to draw attention to the privacy paradox to protect consumers. Finally, the PPM_U reminds consumers themselves of their possible misconduct regarding privacy. With this knowledge, consumers can scrutinize their behavior and protect themselves from unwanted data disclosure.

4.1.6 Evaluation of the privacy paradox metric

The evaluation of design artifacts and design theories is a central part of design science research (Hevner et al., 2004; Peffers et al., 2007). In this paper, the evaluation demonstrates the utility, quality, and efficacy of the *PPM* using an elaborated evaluation method (Hevner et al., 2004). We evaluate the *PPM* against the requirements compiled in Section 4.1.3 (“Requirements for the Privacy Paradox Mectic”) to ensure the rigor of the research and to prove the utility of the metrics in real situations.

Quantifiability: To calculate the *PPM*, consumer data are required. In Section 4.1.5.1, we present the possibility of quantifying the input parameters and demonstrate how the variables can be calculated in detail in the context of mobile apps. Additionally, we define the calculation rules to determine the *PPM* resulting in a percentage. Thus, the *PPM* meets the requirement by quantifying the input parameters and the result.

Precision: By specifying the components of the *PPM* and defining its calculation rules (see Section 3.1.4), we ensure its precision during determination and that the measurements are taken under prescribed conditions. This situation also ensures the repeatability of the *PPM* calculation (see Section 4.1.5.2).

Comparability: The result of the *PPM* is a standardized percentage value, which is easy to compare. A “percentage simply converts a proportion to terms of per-hundred units” (Herrmann, 2007, p. 33).

Obtainability: The obtainability of the data depends on the digital service and the context. In the case of mobile apps, all data can be simply collected by conducting a consumer survey. Real consumer behavior concerning data disclosure can also be identified because consumers are only able to install the mobile apps if they accept the permissions and, consequently, release their data.

Interpretability: Because the *PPM* is a percentage, the metric can be interpreted. PPM_U represents the percentage of service users behaving paradoxically, PPM_N represents the percentage of non-service users behaving paradoxically, and the integrated *PPM* describes the share of all consumers who behave paradoxically.

Usefulness: The information provided by the *PPM* brings along several advantages for consumers, companies offering digital services, ICT platform providers, and organizations for consumer protection, such as raising awareness for data privacy, more sensitive data disclosure, and improvement in consumer services. In the context of mobile apps, the interest groups are app users, app providers, app stores, and consumer protection organizations. The usefulness of the *PPM* is discussed in detail in Section 4.1.1. The implications of the *PPM* results are presented in Section 4.1.7.

Economy: Economic value is strongly application-dependent because varying costs and benefits can result from the data collection. The *PPM* is the only metric measuring consumers' privacy paradox, which means that it is currently the best metric that considers the economic aspects of cost and benefit. Therefore, future research should consider these economic aspects when extending the *PPM* or defining new metrics that measure the privacy paradox.

To summarize, we emphasize that the *PPM* meets all requirements in the context of mobile apps. However, we cannot generalize that the *PPM* fulfills all requirements in the context of other digital services. Some requirements are context-sensitive and must be examined before adapting the *PPM* to other fields of application. Given that the metric presented in this study is the first quantification of the privacy paradox, no other privacy paradox metric exists that would outperform the *PPM* on the requirements.

4.1.7 Discussion and conclusion

The privacy paradox is well known in the literature; however, to date, no other approach has measured its extent. To better support the investigation of the privacy paradox, we design the *PPM*. This metric uses the theoretical basis of the privacy calculus and the observation of real consumer behavior to determine whether a consumer behaves paradoxically.

A metric is a human created artifact. We chose a design science research approach and present the metric in terms of a design science artefact to clearly highlight this artificial nature, explicitly specify the general requirements we see for such a metric and present it for both usage and as a benchmark reference for metrics to potentially be designed in the future. We posit that the PPM is a generalizable metric applied to mobile apps as an example of digital services. As such, it contributes to a nascent design theory on quantifying the privacy paradox.

Appendix 4.1.A further details this perspective by discussing the PPM in terms of the components of a design theory as suggested by Gregor and Jones (2007).

The *PPM* provides several important insights and implications for research and different interest groups, including service consumers, companies offering digital services, ICT platform providers such as app stores, and consumer protection organizations. For research, the privacy paradox often represents a major limitation in empirical research towards consumers' privacy intentions. Accordingly, the *PPM* is a tool that may be validating respective research findings and is thereby the first approach to identify and quantify deviations between consumers' privacy intention and behavior. In practice, service consumers could benefit from the *PPM* when being implemented, for instance, as a smartphone application that monitors installations and use of other apps. In this way, the *PPM* could provide transparency about an individual consumer's privacy paradox, which might save consumers from careless disclosure of data and thus unwanted consequences regarding data privacy. Customers typically do not realize privacy invasions at the point of data disclosure but rather as soon as its consequences become apparent. However, at the latter point, not only consumers sustain damage, but also the company offering the respective service, as consumers might be dissatisfied, leave the company, or generate negative word-of-mouth for instance. That is, companies offering digital services can use the *PPM* to identify careless consumer decisions towards data disclosure and manage the risk related to such decisions. More concrete, based on the *PPM*, companies might decide to provide warnings at the point of possible data disclosure and make suggestions of alternative digital services that better fit the consumer's privacy intentions. The data to identify the privacy intention can, for example, be collected during a field study to identify the *PPM* in general, to make a statement for specific customer groups, or while using the digital service. With the help of the privacy intention, the *PPM* can be detected if the behavior does not fit to it. Accordingly, ICT service providers, such as app stores, might use the *PPM* to enhance their attractiveness by providing privacy-customized warnings, suggestions, sorting, or filtering based on the *PPM*. E.g., they can ask the privacy intention of every customer at the first time of using the ICT platform to be able to detect the gap between intention and behavior before it comes to the data disclosure. Consumer protection organizations might, for instance, take the *PPM* as a basis for further empirical studies that increase public awareness on the risks related to the privacy paradox. Beside these stakeholders, society itself can benefit from being aware of the privacy paradox when aiming at "understanding, anticipating, and proposing solutions for potential future negative consequences of ICT" (Lynne & Mentzer, 2014).

Our research is beset with limitations that require further investigation. First, the *PPM* is based on the binary segmentation of consumers in non-service usage ($usage_i = 0$) and service usage ($usage_i = 1$) on the one hand and on their classification into the four quadrants formed by the divisions $\hat{b}$ and $\hat{c}$ on the other hand. Therefore, consumers classified at the edges of these segments could already belong to adjacent ones if they provided slightly different survey responses. Thus, the result from calculating the *PPM* depends on the specifications of the exact boundary values. In this paper, we provide examples, such as using the median for $\widehat{benefit\ threshold}$ and $\widehat{risk\ threshold}$, but there are no definite guidelines. Future research might explore more fine-grained classifications and identify and evaluate alternative divisions. Second, we showed that the evaluation of the *PPM* regarding the seven requirements is particularly based on a single expository instantiation for mobile apps. Future research might apply the *PPM* for other digital services. Thereby, its evaluation might be strengthened and its boundaries tested. Third, the expository instantiation of the *PPM* uses a few simplifications. These simplifications include the aggregation of the apps in categories and assume homogeneity within a category. Further, for simplicity we used equal weights for both benefits and the twelve app permissions for all participants, although the basic idea of the model enables differing weights as well. Additionally, survey participants were not representative of the entire population. Finally, we applied the *PPM* in a research project and, to date, there was no application in an industry situation. For further evaluation, particularly regarding usefulness, a practical application in an industry context would be beneficial.

Overall, we presented the PPM, a privacy paradox metric for digital services, as a design artifact that enables the assessment of consumers' privacy paradox for digital services. We followed the design science research methodology of Peffers et al. (2007) to develop the metric. Based on the context of the problem and the theoretical background, we identified metric requirements and presented the basic idea, form, and functions of the PPM. Furthermore, we demonstrated the practical applicability in the context of mobile apps as an example for digital services and evaluate the metric in terms of quantifiability, precision, comparability, obtainability, interpretability, usefulness, and economy. We hope that this quantitative perspective on the privacy paradox contributes to improvements in the disclosure and the use of private data.

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Appendix

Appendix 4.1.A Components of a decision theory and implementation in the present research

Theory component	**Description**
Purpose and scope	The theory aims to assess the extent of consumers' privacy paradox in the use or non-use of digital services.
Justificatory knowledge	The metric is based on the privacy calculus, which is "the most useful framework for analyzing contemporary consumer privacy concerns" (Culnan & Bies, 2003).
Core constructs	The core constructs of the *PPM* are "digital service," "service benefit," "service risk," and "service usage."
Principles of form and function	The metric fulfills both the design objective and the metric requirements. Based on the theoretical privacy calculus and the observable real usage behavior, the PPM assesses the share of all consumers who behave paradoxically. We propose this assessment as the abstract design for assessing the extent of the privacy paradox.
Principles of implementation	To apply the *PPM* in the mobile app context and to determine the service benefit, we use the constructs included in UTAUT2, namely, hedonic motivation and performance expectancy. Additionally, we utilize the app permissions of the Google Play Store for the service risk calculation. We used the median of the benefit and the risk to classify consumers into segments and calculate the privacy paradox in our practical implementation.
Expository instantiation	We conducted a survey with 715 participants and calculated the *PPM* for five app categories as examples of digital services. Therefore, we present the implementation of the *PPM*, which shows the metric's feasibility.
Testable propositions	The claim has been made that the *PPM* is also applicable to other services. Although the metric is defined for general application, the requirements of the *PPM* must be proven in individual cases.
Artifact mutability	In this paper, we present a general approach for calculating the *PPM* by using several previously fixed parameters, such as consumer classification or service usage realization. The adaptation and evaluation of these parameters are given for further work.

Appendix 4.1.B Uni-dimensional results of the survey

Mean and median of the survey items for determining the benefit of using a specific app type

n=715	Naviga-tion apps	Note apps	Radio apps	Picture editing apps	Running apps
Hedonic Motivation					
Using [app type] is fun.	5.74 / 6	4.74 / 5	3.18 / 3	3.57 / 4	3.28 / 3
Using [app type] is enjoyable.	5.71 / 6	3.54 / 4	1.90 / 1	2.31 / 2	2.63 / 2
Using [app type] is very entertaining.	4.07 / 4	4.12 / 4	2.11 / 1	2.46 / 2	3.01 / 2
Performance Expectancy					
I find [app type] useful in my daily life.	3.66 / 4	2.98 / 3	3.50 / 4	4.02 / 4	3.22 / 3
Using [app type] helps me accomplish things more quickly.	2.95 / 3	2.46 / 2	3.25 / 3	3.89 / 4	2.74 / 2
Using [app type] increases my productivity.	2.78 / 3	2.33 / 2	3.66 / 4	3.86 / 4	2.75 / 2

Distribution of respondents' perceived risk by permission

	Perceived risk						
	strongly disagree						strongly agree
Permission	1	2	3	4	5	6	7
Device and app history	25	34	61	80	122	154	239
Identity	12	12	21	49	94	149	378
Contacts	15	11	20	48	69	156	396
Calendar	28	34	37	76	96	125	319
Microphone	26	38	55	95	95	132	274
SMS	18	17	26	63	94	140	357
Phone	10	12	21	38	89	129	416
Photos/Media/Files	17	28	36	81	83	128	342
Wi-Fi connection information	28	43	52	82	82	106	322
Location	29	32	51	89	84	99	331
Camera	41	58	68	115	106	115	212
Device ID and call information	16	20	38	83	87	141	330

5 General discussion and conclusion

The following chapter presents the results of this dissertation in Section 5.1, an outlook on future research in Section 5.2, and a brief conclusion in Section 5.3.

5.1 Results

This dissertation focuses on the digitalization of the individual. In detail, the consequences thereof as perceived by individuals, the design options available to organizations to address these consequences, and the question as to how all of the above influences the behavior of the digitized individual. After motivating the topic and giving an overview of the applied framework of Matt et al. (2019), the five research papers provide new models and approaches for the research objectives outlined in Table 1-1. These research papers are divided into three parts: consequences, designs, and behaviors. The subsequent sections cover the key findings of the respective research papers.

5.1.1 Results of part A: Negative consequences of digitalization for the individual

Part A discusses the consequences of the digitalization of the individual. The research articles P1 and P2 focus chiefly on the negative consequences. They show in two different domains what concerns individuals about using digital technologies and what prevents individuals from using them.

P1 (Section 2.1) identifies 10 major concerns about the underlying technology, data, or the decision-making and 14 concerns about consequences that individuals perceive when using ADM in their daily lives. After introducing the theoretical background of algorithmic decision-making and concerns, P1 gives a detailed insight into the research methodology and approach. A structured literature review was first conducted to identify the concerns towards ADM in prior literature. Therefore, we defined a search string with the respective terms and examined five databases. 18 research articles were deemed to be relevant. Next, 13 semi-structured interviews were conducted, which are based on five ADM use cases, to confirm the concerns from the literature review and discover further concerns about ADM. All interviews were transcripted and subjected to qualitative content analysis. The overall results of P1 are 24 concerns, divided into two categories: concerns that are inherent to the technology, data, or decisions, and concerns that do not necessarily have a direct impact but can lead to specific concerns about consequences. All of these concerns and how they affect one another were discussed in detail. The interviews further revealed several aspects that mitigate individual concerns about ADM, such as transparency and trust. The interviewees also mentioned potential positive aspects of ADM, including time savings, reduced effort, diminished subjectivity, increased fairness in decisions, greater variety and pleasant surprises through ADM, and a lower error rate in decision-making. In short, this framework facilitates the development of responsible and transparent ADM-related offers and services that take account of the fears and concerns of the individuals and contributes to the literature on the dark side of IS.

P2 (Section 2.2) takes a qualitative research approach to examine the inhibiting factors of individuals when adopting digital technologies. 26 interviews were conducted with healthcare professionals and patients to identify those factors. This research paper presents 11 hindrance factors structured in four categories: user, digital technologies, data, and resources. P2 provides new insights into the technology adoption in healthcare and expands the digital transformation framework created by Vial (2019). Some of the hindering factors discussed in the interviews are not new and were already discussed in prior literature in the context of the increasing digitalization of healthcare, such as the unreliability and complexity of digital technologies, discrimination, invasion of privacy, or data manipulation. Further, this study goes beyond the prior literature and compares the hindering factors that beset healthcare professionals as opposed to those affecting patients. However, the results show that the healthcare professionals' and patients' perceived concerns do not differ, there are differences in who is influenced by the hindrance factors. Whereas patients are more affected by data manipulation, data fixation, invasion of privacy, and discrimination, healthcare professionals tend to be impacted by the factor "losing autonomy to act." The concerns about the superpowerful health insurances, the unreliability of DTs, the complexity of DTs, and financial and time effort have a bearing on healthcare professionals as well as on patients. Another result of P2 is the discussion on integrating the hindering factors perceived by individuals into the Unified Theory of Technology Acceptance (UTAUT) by Venkatesh et al. (2003). After all, the 11 hindering factors identified in P2 influence the four main constructs of the UTAUT. Consequently, each of the hindering factor inhibits an individual's behavioral intention to use digital technologies and negatively impacts the usage behavior. In summary, the results of P2 offer guidelines to service providers and managers in the healthcare sector. Digital transformation in this sector is a sensitive topic as multiple user concerns can complicate or inhibit its adoption. Considering the framework developed in P2 will help to address these hindering factors and promote digital transformation.

5.1.2 Results of part B: Design approaches for information systems in organizations

Part B presents design approaches for information systems that organizations can use to address individuals' perceived consequences and change their behavior using digital technologies. Both papers in part B present quantitative decision models as decision support for organizations.

P3 (Section 3.1) develops a quantitative decision model to help decide whether to integrate customers into business processes by considering the necessary customer support. In addition, a way to calculate customer support was presented. This is essential, as for many organizations the economic effect of SSTs and the associated necessary customer support is still unclear. Thus, decisions were made without an economic basis. By considering the customer group (which depends on the customer's process knowledge and technology affinity) and their need for support, organizations can avoid further expenses, such as costs for additional support or financial losses due to customer churn. Further, the practical application is demonstrated by a case study. With that, P3 complements prior research in SSTs that had merely considered single effects such as productivity, efficiency, or customer satisfaction when making decisions about customer self-service. The model developed in P3 allows making economically well-founded decisions when introducing SSTs by considering both perspectives, the process and the customer perspective. In other words, it addresses the critical dimensions of the impact of SSTs.

P4 (Section 3.2) develops a formal decision model which decides with the help of an economic basis on customer recovery investments. To calculate the threshold at which it becomes economically reasonable to invest in an individual customer relationship, the probability of whether a customer relationship is "alive," "dying," or "dead" has to be considered. Accordingly, "dying" customers are those whom the organization wants to recover, whereas "dead" customers are beyond recovery as the effort involved would make the relationship unprofitable. A customer relationship is economically reasonable when the present value of future cash flow when investing in the recovery of a customer relationship is higher than not investing. The quantitative decision model was evaluated by way of an exemplary case, a sample calculation, and a sensitivity analysis. This latter shows that the probability of a customer relationship being "alive" has to be estimated carefully as an estimation error causes disproportionately large changes in cost savings. However, even with less well calculated estimates, cost savings with a lower percentage can be achieved. The practical use is born out in expert interviews. In the first part of the interviews, the interviewees reveal that, at present, no organizations are using a quantitative decision process for investments in customer recovery. Most keep customer recovery very simple and only a few make their decisions based on statistical estimates and economic calculus. In the second part of the interviews, it is apparent that organizations consider it important to distinguish between “alive,” “dying,” and “dead” customers, and that the probabilities of these customer statuses ought to be calculated. Using the model developed in P4 allowed them to easily determine the relevant calculation variables, and experts stated that the model provides good decision support for organizations.

5.1.3 Results of part C: Behavior of individuals in a digital world

Part C investigates the behavior of individuals when using digital technologies. Research paper P5 (Section 4.1) uses a newly developed metric to better explore the privacy paradox – the irrational inconsistency between the actual behavior of individuals and their theoretical concerns about the disclosure of their private data when using digital technologies. The metric is derived from the design science research methodology. The PPM uses the theoretical basis of the privacy calculus – the rational risk-benefit trade-off for deciding whether or not to disclose personal information – and the observation of actual consumer behavior to determine if a consumer behaves paradoxically. As such, it is the first quantitative measure of the extent of the privacy paradox. To develop this metric further, P5 establishes requirements it must fulfill to guarantee high quality, in particular quantifiability, precision, comparability, obtainability, interpretability, usefulness, and economy. Additionally, with the data from a survey conducted with 715 participants from the largest universities in Germany, it was possible to test an exemplary application of the PPM that uses mobile apps in a use case of digital services. The application reveals that many individuals use a mobile app even though they perceive only minor benefits as opposed to significant risks. There is, however, a difference between hedonic apps and performance apps as the latter are used more often when a significant risk outweighs a minor benefit. As this example shows, the PPM offers considerable advantages to researchers and individuals as well as organizations that provide digital services, ICT platform providers, and consumer protection organizations. Seeing as it makes the privacy paradox transparent, it also allows consumers to prevent careless data disclosure and unwanted consequences. At the same time, organizations can use the PPM to identify irresponsible consumer decisions regarding data disclosure and manage the associated risks. Consumer protection organizations can increase public awareness of these risks, and ICT service providers can use the PPM to enhance their attractiveness by providing customized warnings, suggestions, sorting, or filtering. In summary, the PPM offers a quantitative perspective on the privacy paradox and in so doing contributes to improvements in disclosure and private data use.

5.2 Future research

The following sections present starting points for future research in the areas explored in the five research articles contained in this dissertation. These starting points also throw into relief the limitations of each article and how to go beyond them.

5.2.1 Future research regarding part A: Negative consequences of digitalization for the individual

The two articles in part A focus on the identification of the concerns that individuals have about ADM (P1) and technology adoption in healthcare (P2). This covers two important domains of digitalization, yet future research may do well to examine further, and also more concrete, use cases and research areas. Furthermore, while identifying the concerns in different application domains is crucial to increasing the adoption of digital technologies among individuals, future research may develop countermeasures to mitigate or indeed eliminate the concerns. Another point worth noting is that both studies were conducted in a single country, Germany. Future research may apply the framework with samples characterized by different geographic attributes.

In Section 2.1, research paper P1 has certain limitations. First, although we included open-ended questions regarding the concerns that individuals may have about ADM at the beginning of each interview, future research may pursue this further to achieve higher generalizability or test the concerns for specific use cases. Second, future research may build on this study by developing appropriate countermeasures that address the concerns of individuals. Those concerns can then be better managed to further reduce reservations about ADM and improve its acceptance. Already, there are attenuating and positive aspects to the concerns, as the results of P1 indicate. Future research in the development of ADM systems may find it helpful to investigate which other concerns might be dealt with by further developing their mitigating aspects.

In Section 2.2, research paper P2 presents a framework with some limitations that may stimulate further research. First, it was not the purpose of P2 to achieve statistical validation but to discover patterns to develop a theory and better understand the hindering factors that individuals perceive when thinking about the adoption of digital technologies in healthcare. Future research may collect quantitative data to test and clarify the findings and analyze the interplay among the concerns in greater detail. Furthermore, although we addressed concerns about integration into the UTAUT, we focused on identifying those concerns. Future researchers would do well to treat this UTAUT integration as a good starting point for efforts to foster technology adoption in healthcare.

5.2.2 Future research regarding part B: Design approaches for information systems in organizations

Part B presents two design approaches in P3 and P4 that organizations can implement to deal with the concerns and behaviors of individuals digitalization. Future research may treat these two approaches as starting points to develop further design approaches, for example, to address specific concerns about digital technologies, for which part A already provides numerous pointers. Another possible avenue for future research may be the evaluation of design approaches in terms of their impact on the behaviors and concerns of individuals.

P3 (Section 3.1) offers the following opportunities for future research, mainly due to the elicitation of data for the quantitative decision model. First, the determination of the parameters can involve extensive effort and thus high costs. Future research may focus on finding an easier way to determine those parameters, especially for large companies with many customers. Second, to test the practicability of the decision model, P3 provides a case study of a fictional global travel solutions provider for business customers. Future research may employ the model in real-world contexts and refer to empirical data. Third, customer support is highly dependent on the customer’s technology acceptance, and the survey data presented in P3 shows that the interviewed customers have a comparatively favorable attitude to technologies. This does not, however, represent society at large. Therefore, organizations first have to examine their customers’ attitudes to technology and then decide how to deal with less technology-affine customers and how to motivate them to use self-service.

P4 (Section 3.2) presents a decision model with certain limitations that stimulate further research. The model has already been evaluated by way of expert interviews and an example calculation. However, future research may apply the decision model in a real-world context to assess its usefulness more precisely. It is also worth noting that the decision model is designed to cover a single period. To ensure maximum customer recovery on a permanent basis, future research may extend the decision model to multi-period assessments. Another issue to address is that P4 is based on an organization’s risk neutrality. In reality, an organization’s decisions are subject to different risk attitudes. Future research may deal with this difference by considering context or branch-specific risk attitudes when deciding on customer recovery investments. Finally, there is an issue with the assumption that investing in a customer relationship deemed to be “alive” is not reasonable in terms of the recovery effect. However, recovery investments could also increase customer satisfaction for “alive” relations. Future research may examine this effect.

5.2.3 Future research regarding part C: Behavior of individuals in a digital world

P5 (Section 4.1) has certain limitations, starting with the issue of model definition. Customers are classified into defined segments based on their service usage and their perception of the benefits and risks associated with a digital service. This classification is done by way of binary segmentation of customers who use the digital service and customers who do not. Meanwhile, the median is used to divide customers according to how they perceive benefits and risks. This method of using the median is, however, merely an example and not a definite guideline. Consequently, the calculation of the PPM depends on the choice of the boundary values. Depending on the segmentation, customers may be classified into one of these segments, albeit at the edge, and yet if they provided only slightly different survey responses they would belong to the adjacent segment. Future research may identify and evaluate alternative divisions or evolve more detailed classifications to measure the PPM. Further, the practical application is based on mobile apps as a single example of digital services. Future researchers may apply the PPM to other digital services. In doing so, they would extend the PPM’s evaluation and test its boundaries. Another point worth noting is that the practical application aggregates the mobile apps into categories that simplify the implementation. This requires homogeneity within an app category. Future research may seek ways to account for this simplification. The following limitation also refers to the implementation of the practical application. As it stands, the model allows different weights for the benefits and concerns, but, in the exemplary application of the PPM, equal weight was given to the twelve app permissions for all participants, if only for the sake of simplicity. Future research may expand the application in another real-world example. Furthermore, since the online survey was conducted in Germany, it should be noted that the results may vary in different countries and that the demographic attributes of our sample may have influenced the results, as the data collected from 715 participants is not representative of the entire population. Future research may repeat the survey in other countries or with more individuals. Finally, the PPM was tested in a research project. To date, it has not been tested in an industry setting. For further evaluation, especially in terms of usefulness, a practical application in an industrial context may be beneficial.

5.3 Conclusion

In summary, this dissertation contributes to scientific knowledge in research on the digitalization of the individual and thus addresses a subject of fundamental importance in this digital age. The five research papers address questions about consequences, design, and behavior. To do so in a cogent and comprehensive manner, it was necessary to look at the various roles a digitized individual can play, as such a holistic view is essential in researching the digitalization of the individual (Matt et al., 2019). The models and approaches developed in these pages have explored ways in which to improve conditions for the digitized individual at all three levels – consequences, design, and behavior – with equal regard for the individual as itself and the individual as a customer. By focusing on these two roles at the exclusion of three others (the individual as a social being, the individual as an employee, and the individual as a citizen) as differentiated in the framework of Matt et al. (2019), this dissertation makes a contribution to previous work in this area. With this, this dissertation will hopefully play a small part in making organizations and individuals better prepared to adapt to the changed circumstances created by the digitalization of the individual. As this will likely continue apace for years to come, this dissertation will hopefully provide valuable theoretical and practical insights for digitized individuals and organizations.

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