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New Channels for Old Businesses: Examining the Drivers and Obstacles of Mobile Commerce Adoption for Complex Products

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Parts of this thesis will be published together with co-authors in relevant research journals. The undertaken investigations are thus described in plural form.

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"It must be remembered that there is nothing more difficult to plan,
more doubtful of success, nor more dangerous to manage
than the creation of a new order of things."

Niccolò Machiavelli, (1513)

PREFACE

There is a long history of conflict between the innovators and advocates of the established order in all areas of life. Today, the cycle of change has reached a tremendous velocity. In this regard, the launch of mobile devices constitutes one of the greatest disruptions humans have ever experienced. Emma Crowe most recently concluded: "*The adoption rate of mobile is twice that of the internet, three times that of social media, and 10 times faster than PCs".* Mobile devices thus become ever more the center of our life, tailored to our needs. Consumers increasingly demand mobile solutions to manage their daily transactions. Mobile commerce (m-commerce) has therefore recently become an important channel for financial services such as insurances. As described in the above quotation by Machiavelli, this provokes a conflict between an old business and a new channel. It therefore comes as no surprise that the insurance business has struggled to integrate this new channel into their sales portfolio, and also struggled to build an attractive environment that fulfills consumers' needs (Statista, 2013). The reasons seem obvious; insurance policies are complex in nature, and have a service system that has grown over centuries and appears, at least offline, to function perfectly. However, the online world now requires changes in one's thinking. Where policy-related information was provided by an agent in the past, today this is done through a website or app. This requires adjustment in the design of information, to convey the same amount of expertise, quality, trustworthiness or care as a living agent would do. To understand the "how" of this transformation, in-depth knowledge based on evidence is needed. In this thesis I will outline the rising challenge by investigating the reasons and means to overcome m-commerce resistance. Therefore, I will apply the knowledge and methods of psychology as a profound basis to understand consumer behavior. This will give insurance companies the opportunity to provide consumers with the sales environment of their choosing and to keep up with the mobile revolution.

Contents

List of Abbreviations

AVE	*Average Variance Extracted*
BIC	*Bayesian Information Criterion*
CAIC	*Consistent Akaike Information Criterion*
CFA	*Confirmatory Factor Analysis*
CFI	*Comparative Fit Indix*
CG	*Control Group*
CMB	*Common Method Bias*
CR	*Composite Reliability*
CSF	*Complexity-Service Fit*
CTS	*Comprehensive Technological Service*
e-commerce	*Electronic Commerce*
ECT	*Expectation-Confirmation Theory*
EFA	*Exploratory Factor Analysis*
ELM	*Elaboration Likelihood Model*
FinR	*Financial Risk*
FtoS	*Face-to-Screen*
GFI	*Goodness of Fit Index*
HSQ	*High Service Quality*
HVM	*Hierarchical Value Map*
IQ	*Information Quality*
IS	*Information System*
ISSM	*Information Systems Success Model*
IV	*Independent Variable*
LSQ	*Low Service Quality*
m-commerce	*Mobile Commerce*
PEIS	*Perceived Effectiveness of Institutional Structures*
PEOU	*Perceived Ease of Use*
PerfR	Performance Risk
PI	*Purchase Intention*
PR	*Perceived Risk*
PsyR	*Psychological Risk*

PU	*Perceived Usefulness*
RMSEA	*Root Mean Square Error of Approximation*
RSM	*Response Surface Method*
SEM	*Structural Equation Model*
SQ	*Service Quality*
SRMR	*Standardized Root Mean Square Residual*
STTF	*Service-Task-Technology Fit*
TAM	*Technology Acceptance Model*
TGS	*Technology-Generated Service*
TimeR	*Time Risk*
TLI	*Tucker Lewis Index*
TMS	*Technology-Mediated Service*
TTF	*Task-Technology Fit*

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Abstract

Although revenues in mobile retail are continuously growing, mobile commerce for complex products such as insurance lags far behind. A basic reason is consumers' perceived misfit of product and channel characteristics. However, scholars and practitioners have only vague ideas of the causes for this misfit. This prevents the development of adequate means to overcome consumer resistance. The present thesis confronts this shortcoming by systematically investigating the psychological mechanisms which produce reluctance, as well as the appropriate countermeasures to facilitate its adoption. In order to do this, four studies with mixed method approaches have been carried out; two studies cover the sources of m-commerce resistance, and two cover the means through which such resistance can be overcome.

Study 1 examines and identifies key antecedents of channel choice based on field data. A synthesis of three fundamental theories was undertaken to pinpoint associated cognitive processes. Product complexity and expertise were found to be key determinants in this context. A quadratic moderating role of product expertise is shown to regulate the extent to which complexity enters the purchase decision. Subsequently, Study 2 examines the cognitive processes underlying resistance in m-commerce. Therefore, consumers' cognitions were mapped and structured by using the laddering interview technique. This revealed hierarchical value linkages. Poor service and system components were the main reasons of customer resistance. In a field evaluation, Study 3 elaborates the understanding of resistance emergence and explores effective countermeasures by applying a set of four statistical analyses. A structural investigation of the concept of risk indicated that psychological risk concentrates the impact of other risk dimensions and acts as mediator towards purchase intention. The induction of service quality moderated the negative effect of risk on purchase intention in a quadratic fashion (inverted-U), leading to minimal risk influence for low and high service quality, but high influence for modest service quality. A laboratory experiment in Study 4 finally presents ways of how to configure service in m-commerce to efficiently support its adoption. Based on task-technology fit considerations, the findings propose a hybrid service approach which combines human-technology mediated and mere technology generated service to leverage the synergies of both. The theoretical and practical implications of all four studies are discussed.

1. Introduction

Mobile devices have become the gateway for communication, our daily assistant and central media source, our wallet and entertainment hub tailored to our preferences. The “anywhere, anytime” connection has a considerable influence on the behavior of consumers. This drives the desire to access products at consumers’ choosing, implying a multi-channel offer (Neslin et al., 2006; Wallace, Giese, & Johnson, 2004), with increasing preferences to access products on mobile devices (Mallat, Rossi, Tuunainen, & Öörni, 2009). The varied capabilities of mobiles hold great potential to facilitate future product purchases and to satisfy consumers’ demands. This potential can also be exploited by complex businesses such as insurance. Smartphones, for example, provide the possibility of remote and instant insurance booking (e.g. booking travel insurance at the airport), without requiring an insurance agent (Laukkanen, Sinkkonen, Kivijärvi, & Laukkanen, 2007; Mallat, 2007). Contracts and transactions can easily be arranged, altered and monitored on the move. This paves the way for real-time and highly personalized insurance products with lower prices. On the provider side, m-commerce can reduce the labor costs, support rapid services with short response times, enable standardization and control for the consumer contact, facilitate the amendment of insurance conditions, extend the market reach due to seamless market coverage and low market entry barriers and provide smart data to improve the service (Hanzaee & Karimian, 2011). Consistent with these benefits of m-commerce, insurance companies currently have recorded a substantial drop of agents caused by the digitalization of commerce (DIHK, 2016).

1.1 Problem Statement

Despite this clear emerging trend in favor of e- and m-commerce, insurance companies still lag behind other businesses (i.e. retail) regarding m-commerce adoption. In a recent evaluation, consumers rated insurance as the second least attractive business for mobile commerce (Statista, 2013). This mainly stems from the inherent high complexity of insurance policies, which require consumers to make a considerable effort to understand the contractual details. The integration of digital channels into the sales portfolio of insurance thus poses a great challenge (Devlin, 2007; Keh & Sun, 2008; Kuisma, Laukkanen, & Hiltunen, 2007), which has not yet been solved. A key reason for this is the lack of empirical knowledge on how to align the traditional products in the insurance sector with the new characteristics of mobile commerce. While traditional offline service delivery in insurance has had centuries to mature and optimize the consumer contact (Froehle, 2006), m-commerce has arisen in a fraction of this time. Today, the sophisticated service level of the offline business has therefore not been reached for the online business. In response, consumers have evolved a two-step product encounter called ROPO. ROPO defines the “research online, purchase offline” principle that describes the exploration of a product online and the subsequent purchase offline, which is particularly noted for complex products (Heil, Lehmann, & Stremersch, 2010; Jin, 2012). This suggests that consumers lack confidence in buying insurance products online without personal assistance. To provide consumers with sufficient confidence for an unassisted product purchase, extensive research in this area is needed (Collier & Kimes, 2012). In the following section, I will give a brief literature review, to outline the central objectives of this thesis.

1.2 Theoretical Background

1.2.1 Sources of M-Commerce Resistance

Previous literature identified several factors which cause resistance to switch channels (Burnham, Frels, & Mahajan, 2003; Samuelson & Zeckhauser, 1988; Yang, Pang, Liu, Yen, & Tarn, 2015). Of these factors, product complexity has been found to be a key concern regarding new channel adoption (Burnham et al., 2003; Simon & Usunier, 2007). Product complexity is defined as the extent to which a consumer perceives a product as difficult to understand and use (Rogers, 1995) and is mainly determined by the intricacy of process steps and the product diversification (Simon & Usunier, 2007). In general, increasing complexity was found to reinforce risk perceptions (e.g. time risk or financial risk) during the product encounter (Maity & Dass, 2014). Scholars also argued that this can be compensated for by a consumer’s expertise. Studies in this context have mainly focused on channel expertise (i.e. e-store experience; Falk, Schepers, Hammerschmidt, & Bauer, 2007), but widely disregarded the impact of product expertise. In the insurance business, product expertise is a profound differentiator that can serve to facilitate the adoption of new channels by providing the consumer with self-confidence (Petty & Cacioppo, 1986; Tesser, 1978; Van Beuningen, de Ruyter, Wetzels, & Streukens, 2009). In contrast, established psychological theories suggest decreasing willingness to adopt new channels with higher levels of product expertise due to higher switching barriers. The status quo bias theory summarizes several effects that cause people to maintain a given status or situation (Samuelson & Zeckhauser, 1988). For example, as noted by Kahneman and Tversky (1982), people overestimate the feelings of regret when a new channel fails to be advantageous compared to a former channel, leading to regret avoidance behavior. The elaboration likelihood model (Petty & Cacioppo, 1986) states that people engage in diverging information processing styles depending on the amount of experience. This entails a rather systematic (central) or a rather heuristic (peripheral) processing. To explain the key mechanisms that determine the resistance towards mobile insurance, it is necessary to solve incongruences and to align theories in the literature by examining the influence of complexity in channel choice decisions and how expertise alters its influence.

While product complexity is a vague term for numerous attributes such as product intangibility, lack of transparency, complex handling or the variety of product and price options (Devlin, 2007; Keh & Sun, 2008; Murray & Schlacter, 1990; Yu & Tung, 2014), it basically lacks precision for mobile insurance. This especially applies to the concrete attributes that define complexity and could thus be the linkage to overcome adoption hesitance. Studies in related areas, such as online payment, reported consumers complaining about handling problems, a lack of receipt, unclear proceedings or insufficient information (Kuisma et al., 2007). In addition, channel characteristics such as constraint bandwidth, battery power and screen size were found to hinder m-commerce adoption (Cao, Lu, Gupta, & Yang, 2014). The means-end approach (Reynolds & Gutman, 1988) is one of the most promising developments in market psychology to understand consumer behavior (Grunert, Beckmann, & Sørensen, 2001). Building on the expectancy-value theory (Rosenberg, 1956) it provides a hierarchical concatenation of attributes (means) with directly and indirectly associated consequences (i.e. time effort), which ultimately prevents the pursuit of individual values (i.e. self-actualization). This approach opens the door to understanding resistance and should be investigated in the context of m-commerce to identify the ladders of resistance and to classify central barriers in order to overcome the adoption inertia.

1.2.2 Means to Mitigate M-Commerce Resistance

The complexity of insurance products drives the perception of risks associated with the contractual process, which thus constitutes a key barrier to enter m-commerce. A promising approach to lower those entry barriers comes from the provision of high service quality (Grewal, Iyer, Gotlieb, & Levy, 2007; Mitchell & McGoldrick, 1996). This can be defined as the extent to which a mobile sales environment facilitates efficient and effective purchases (Zeithaml, Parasuraman, & Malhotra, 2002) and is reflected by the dimensions of reliability, responsiveness, assurance, empathy, and tangibility. It stems from the assessment of the service a company should offer (i.e. expectation) compared to its actual service performance

(Parasuraman, Zeithaml, & Malhotra, 2005). Referring to the information systems success model (ISSM), service quality, next to system and information quality, is a key driver of web quality and determines the success of information systems (IS; Delone & McLean, 2003). Scholars found service quality to increase the understanding of products and to improve consumers' perception of skills when engaging in online environments (Ding, Hu, Verma, & Wardell, 2010; Sweeney, Soutar, & Johnson, 1999). It thus reduces buying-related risks and empowers people to use m-commerce. Nevertheless, scholars recently predicted several limitations concerning the benefits of service quality, meaning that it harms the willingness to transact when it crosses a certain level. This was proven for well-established retailers such as Amazon and Ebay (Gefen & Pavlou, 2012), where numerous service features can hinder a fast and efficient product purchase. This, however, only covers a small field of e-commerce. It remains unclear, how service quality plays a role within the purchasing of highly uncertain and complex products such as insurance in a mobile environment.

A second relevant research area to reduce m-commerce resistance embraces the designing of service in mobile channels. Although service is known to have positive effects, knowledge about the appropriate composition of service is rare. Likewise, managers often assume that online service requires similar attributes as personnel offline service (Froehle, 2006). However, this assumption lacks scientific evidence and needs to be challenged when applied to m-commerce. Scholars argue that service has to be matched to the richness of information a channel provides (Froehle, 2006; Maity & Dass, 2014). For m-commerce two types of service can be distinguished, namely technology mediated (TMS) and technology generated service (TGS). The first involves employee assistance via a technological medium such as mobile devices. Typical forms are the consumer contact via telephone, chat or email. In contrast, technology generated service provides only technological service without direct personal support. Well known forms are the FAQs, test seals or product ratings. Together, both are referred to as face-to-screen service (as opposed to the face-to-face service typical of offline markets). Recently, scholars have questioned the superiority of both personal mediated or technical generated service (Simon & Usunier, 2007), but proposed a combined "hybrid" approach to foster synergetic effects (Selnes & Hansen, 2001). By drawing on the task-technology fit theory (Goodhue & Thompson, 1995; Larsen, Sørebø, & Sørebø, 2009), a combination of both services appears reasonable, as it best suits the evolved ROPO principle of consumers. More precisely, the consumers' tendency to explore products online can be best covered by comprehensive information offer as provided in TGS. Remaining uncertainties and queries can then be clarified by using TMS. In extension to the task-technology fit theory, this suggests integrating service as a third aspect of fit, which needs to be considered when designing mobile sales environments. However, the effect of different types of service in m-commerce is empirically unexplored. In the next section, based on the theoretical overview, central research objectives are defined.

1.3 Research Objectives

The present thesis aims to obtain a comprehensive understanding of the mechanisms that determine m-commerce resistance for complex products and to generate countermeasures that mitigate the prevailing adoption inertia. A set of four studies is conducted to encounter the mentioned research gaps by advancing the IS research in two areas, targeting (a) the *sources of m-commerce resistance* in study 1 and 2 and (b) the *means to merge insurance and m-commerce* in study 3 and 4.

In the course of this thesis the following research questions will be answered: **Study 1** addresses the emergence of resistance and answers the questions of why more complex products appear to be less suitable to m-commerce and why people with higher product expertise show higher values of resistance. **Study 2** concretizes the emergence of resistance by identifying the concrete barriers of m-commerce. This answers the question of which attributes are problematic for the adoption of m-commerce and what the reasons are. **Study 3** is dedicated to the potential of service as a countermeasure to m-commerce resistance. This answers the questions of whether service can help to mitigate risks and to improve the purchase intention in m-commerce and which extent is needed to reach the best outcome. Finally, **Study 4** deepens the knowledge about the potential of consumer service by testing various configurations of service types in m-commerce. This answers the question of how service in m-commerce needs to be designed to facilitate an effective purchase. The following section specifies the structure of this thesis comprising a general overview of the hypothesis and study design.

1.4 Thesis Structure

The present thesis is divided into six chapters, whereof each study forms one chapter, embraced by two chapters for the introduction and a conclusive discussion. In **chapter 2** a quantitative field study is presented to identify the psychological mechanisms, which stimulate resistance towards m-commerce. A synthesis of expectation-confirmation theory, status quo bias theory and elaboration likelihood model is performed to examine consumers' processing of information that underlies channel choice. The subsequent evaluation is split into two parts: In the first analysis, the channel preferences (in terms of purchase intention) for m-commerce, agent and e-commerce with respect to different amounts of product complexity and consumer expertise are compared. It is hypothesized that varying levels of complexity and expertise generate different preference profiles. To address the assumption, group comparisons for a large sample of participants with random assignment to insurance products of different complexity were calculated. In the second analysis, these assumptions are further differentiated, by hypothesizing an interaction between expertise and complexity. It is argued that expertise alters the way complex product information is processed, selected and evaluated. Therefore, the group data are merged and analyzed by applying polynomial equation modeling and by investigating the response surface.

In **chapter 3** an exploratory qualitative interview study with insurance customers is conducted to map the cognitions that determine m-commerce resistance. A literature review and a qualitative means-end approach are undertaken to identify the hierarchical linkages between the attributes of m-commerce in the insurance sector, emerging functional and psychosocial consequences and terminal conflicting consumer values. The interviews are based on a laddering interviewing technique to extract “ladders” of resistance by using a probing questioning approach. All emerging ladders are coded following a derived categorical scheme consistent to the attributes, consequence and value structure. Drawing on the resulting implication matrix a hierarchical value map visualizes the most salient paths to resistance. Finally, to integrate the results into recent IS literature, attributes are associated to the three determinants of IS success capturing system, service and information related aspects.

In **chapter 4** the implementation of service quality in m-commerce is considered as a highly promising approach to reduce resistance towards mobile insurance. Based on a quantitative field study, this assumption is analyzed in four ways. First, a structural equation model serves to test positive impact of service quality on the perception of risks and the purchase intention in m-commerce. This also includes an investigation of the structure of the main risk dimensions. The second to third analysis challenges recent findings, which suggest limited benefits with increasing amounts of service that is provided. It is hypothesized that the limits of service quality vary in dependence of the context in which it is applied, and does not hold true for complex services in m-commerce. Therefore, a persisting positive effect of service on risks is tested by applying polynomial equation modeling and by analyzing the response surface. Lastly, a between-group design is conducted to explore if differences result for groups with high service quality and low service quality. This is accomplished by exposing participants to a high and a low service condition through presentation of deviating versions of mobile applications.

In **chapter 5** appealing forms of service to facilitate m-commerce are discussed. Drawing on the theorizing of the task-technology fit theory and the observed ROPO behavior of consumers, it is hypothesized that neither technical mediated nor technical generate service alone are efficient enough to support m-commerce. More appropriately, a combination of both in a hybrid approach is suggested to satisfy consumers' needs. This challenges prevailing views which persistently favor personal consumer service across channels. The presented argumentation leads to the conclusion that service has to be incorporated in the task-technology fit approach as third relevant variable to increase IS success. This is tested by executing a laboratory experiment and providing consumers with different forms of service. The manipulation is based on an exclusively programmed app, which was slightly altered in terms of the dominant service features that are presented in each condition.

Finally, **chapter 6** provides a conclusive discussion of the results found in the frame of theoretical and practical implications. Based on the gained insights and the limitations of the applied methods, opportunities for follow-up investigations are discussed. The thesis closes with an outlook.

STUDY 1

2 The Impact of Product Complexity on Channel Choice Behavior and the Moderating Role of Product Expertise

2.1 Abstract

Multi-channel strategies are becoming increasingly important, but are struggling for acceptance in markets with complex products. In this regard, literature lacks sufficient understanding of the sources of adoption resistance towards new channels. The goal of this study is to fill these gaps by explaining the basic psychological processes that determine channel choice for complex products. Based on the synthesis of expectation-confirmation theory, status quo bias theory and elaboration likelihood model product complexity and expertise are examined as key antecedents for channel choice behavior. Moreover, an interaction effect between complexity and expertise is hypothesized. The results confirm that both variables alter the channel preferences in terms of the respective purchase intention. A quadratic moderation effect further indicates that a-priori expertise alters the way complexity is processed with significant outcome changes in the perceived risk. The results provide an enhanced theoretical basis for future research and yield practical implications to reconcile channel, product and consumer characteristics.

2.2 Introduction

The ongoing "explosion of multichannel retail" (Avery, Steenburgh, Deighton, & Caravella, 2012, p. 96) yields new opportunities and challenges for providers as well as consumers. The latter have become more and more demanding, selective and search for flexibility concerning their shopping behavior. This trend also comprises complex businesses as insurance (Devlin, 2007). Thus, established enterprises such as Allianz, AXA and AIG have extended their distribution channel portfolio from brick and mortar sales via agent to brick and click sales via e- and m-commerce for quite a while (Yang, Lu, & Chau, 2013). Nonetheless, insurers are facing acceptance problems in the online business on the consumers' side (Devlin, 2007; DIHK, 2016).

The literature on channel choice behavior has raised considerable interest in the past decades (Yang et al., 2013). Particular attention was drawn to product and channel characteristics such as service quality (Mallat et al., 2009, Maity & Dass, 2014) as well as consumer characteristics such as age (Meuter, Bitner, Ostrom, & Brown, 2005, Simon & Usunier, 2007) and the interaction between these variables (Dabholkar & Bagozzi, 2002; Maity & Dass, 2014; Muthitcharoen, Palvia, & Grover, 2011; Swaminathan, 2003). Other studies considered processes and outcomes of channel encounters such as the emergence of risks and satisfaction (Gupta, Su, & Walter, 2004a; Montoya-Weiss, Voss, & Grewal, 2003). The majority of investigations, however, neglect the elementary aspects of channel choice before risks are emerging. In this context complexity has been confirmed to be one of the most persistent predictors of technology resistance (Burnham et al., 2003; Johnston & Lewin, 1996; Meuter et al., 2005; Simon & Usunier, 2007; Teo & Pok, 2003; Wu & Wang, 2005). Nevertheless, recent studies have revealed a varying impact for product complexity, posing some incongruences. This incluses positive associations for product complexity and channel choice (Maity & Dass, 2014) as well as non-significant influences (Simon & Usunier, 2007). In this regard, the expertise[1] a consumer exhibits has been named to alternate the effect of complex information (Alba & Hutchinson, 1987; Petty & Cacioppo, 1986) and the willingness to approach new channels (Samuelson & Zeckhauser, 1988). Reasons for this might be the altered information processing, selection and evaluation. The majority of studies in this area are devoted to internet expertise (Falk et al., 2007; Frambach, Roest, & Krishnan, 2007; Hernández, Jiménez, & Martín, 2010), but few considered the role of product expertise (Swaminathan, 2003). However, for complex products, the latter may be pivotal in adopting new channels due to its direct relevance to master product complexity. The investigation of product complexity by taking product expertise into account is thus assumed to solve prevalent incongruences about the role of both variables. This article accordingly explores the channel choice behavior as a function of product complexity and expertise.

Our theorizing is based on three fundamental theories: Firstly, drawing on the expectation-confirmation theory (ECT; Oliver, 1980) complexity is identified as a basis of channel selection by stipulating the channel service performance that is demanded to relieve uncertainty in the purchase process. This influence aggravates with higher levels of expertise as a consequence of higher expectations. Secondly, the status quo bias theory (Samuelson & Zeckhauser, 1988) is applied to shed light on the hesitance to adapt concurrent channels due to biased perceptions that are reinforced by higher levels of expertise. Thirdly, based on the elaboration likelihood model (ELM; Petty & Cacioppo, 1986) it is theorized that the impact

[1] In the introduction we used the term “expertise” representative for the constructs of expertise and experience.

of product complexity on channel acceptance varies for novices and experts as a matter of divergent processing, selection and evaluation of information.

The present article will enhance recent literature and practice in three ways: Firstly, the study transfers the potential of basic psychological theories to the multichannel research. This synthesis enables a thorough explanation about the mechanism that causes reluctance towards new channel adoption by taking detrimental effects into account. This strengthens the fundament of research in this area and deepens the understanding of decision making in channel choice settings. Secondly, our investigation substantiates the role of complexity in channel selection by considering interaction effects. This advances theory and practice by allowing the prognoses about channel adequacy for certain products and a proper calibration prior to market launch. Thirdly, the consideration of product expertise complements the broad literature about internet expertise. This enables a clearer differentiation between the types of expertise and sheds new light on inconsistent effects such as varying effects of internet expertise for different purchase stages.

The remainder of this article is organized as follows: In section 1 a literature review is conducted to derive the conceptual foundation and develop corresponding hypotheses as presented in section 2. In section 3, the research design will be introduced and empirically tested in a field study. The results are reported in section 4. The paper closes with a discussion of theoretical and practical implications, limitations and future research recommendations in section 5.

2.3 Theoretical Background

2.3.1 Multichannel Research.

A multichannel strategy can be defined as a marketing strategy, which is characterized by the operation of two or more distribution channels simultaneously (Rittinger, 2014). For example, a retailer can provide products via agent, stationary internet (e-commerce), catalog or telephone. While catalogs' share of sales has declined, sales via mobile devices (m-commerce) have gained considerable importance (Rittinger, 2014) and are controversially discussed in terms of their future meaning and potential. This thesis explores this trend and considers the two main channels in insurance, namely "brick and mortar" sales via agent and e-commerce together with m-commerce.

2.3.2 Complexity.

Product complexity is defined as the extent to which a consumer perceives a product as difficult to understand and use as captured by the diffusion of innovation theory (Rogers, 1995, p. 16). It refers to (1) the intricacy of steps that have to be undertaken to buy the product and (2) the service divergence, determining the amount of options that are available in the purchase process (Shostack, 1987; Simon & Usunier, 2007). Insurance policies embody a prototypical example for such complex products since they are intangible and difficult to evaluate (Devlin, 2007; Keh & Sun, 2008). Typical attributes are lengthy and incomprehensive policies, huge amounts of required data, numerous choice options and premium models, exception clauses or law and tax conditions. Complexity obtained the most consistent explanations for information system (IS) adoption along with compatibility and relative advantage (Mallat, 2007; Teo & Pok, 2003; Tornatzky & Klein, 1982; Wu & Wang, 2005). Previous investigations identified several factors influencing the tendency to switch among shopping channels. Among those are channel risk perceptions, search effort and evaluation effort (Gupta et al., 2004a). These factors are engendered by the complexity a product holds (Keh & Sun, 2008; Loewenstein, 1999; Rogers, 1995) and influence channel choice behavior (Johnston & Lewin, 1996). In line with this, scholars argue that higher levels of complexity evoke higher levels of risk perception (Johnston & Lewin, 1996; Maity & Dass, 2014; Simon & Usunier, 2007). Complexity thus plays a pivotal role in predicting channel retention.

2.3.3 Expertise.

There is an extensive range of studies dealing with expertise and related concepts in IS research (Alba & Hutchinson, 1987; Gefen, 2000; Hill & Beatty, 2011; Karimi, Papamichail, & Holland, 2015; Swaminathan, 2003; Van Beuningen et al., 2009). Such related concepts are product experience, knowledge, familiarity and self-efficacy. These are often used synonymously, although literature provides a clear distinction. Hill and Beatty (2011) point out that experience refers to what one has done in the past, whereas expertise refers to the active component specified as “the ability to perform product-related tasks successfully" (Alba & Hutchinson, 1987, p. 411). Both constructs are based on prior obtained knowledge through interactions and learnings, what leads to product familiarity. In differentiation, knowledge and familiarity are necessary but not sufficient conditions to engender experience and expertise (Heimbach, Johansson, & MacLachlan, 1989). Finally, self-efficacy captures the subjective belief that people are capable of attaining specific goals. Altogether, these concepts are closely related (Howell, Owen, & Nocks, 1990) and thus allow inferences among them. Expertise was found to alter the way information is processed, evaluated and selected (Alba & Hutchinson, 1987; Park & Kim, 2009; Petty & Cacioppo, 1986; Yang, Hung, Sung, & Farn, 2006). This is of great importance to predict channel selection, in case familiarity in one channel exceeds the others and is widely neglected in prior studies. The influence of expertise on channel maintenance obtains evidence by both the ECT and status quo bias theory. Therefore both models are synthesized in the following.

2.3.4 Independent Variables.

In the classical information systems (IS) literature two central determinants have been established to quantify IS success - attitude and behavioral intention (Bhattacherjee & Sanford, 2006; Ho & Bodoff, 2014). Additionally, Meuter et al. (2005) found that complexity enters the formation of behavioral intention indirectly through mediators. As a relevant mediator, risk perception has proven its relatedness to complexity and has become a pivotal predictor in IS adoption (Gefen & Pavlou, 2012; Johnston & Lewin, 1996; Pavlou, 2003; Zhang, Zhu, & Liu, 2012). More specifically, psychological risk occupies a superordinate role among further risks in predicting transaction intention (Keh & Pang, 2010; Stone & Grønhaug, 1993). Apart from the dominating part of literature that employed attitude and behavioral intention as independent variables (IV), the focus on risk could give new insights about the emergence of channel maintenance behavior. In conclusion, the construct of psychological risk next to purchase intention was applied as IV in this article.

2.3.5 Expectation-Confirmation Theory.

The ECT theorizes the continuous process of generating performance expectations and comparing it to actual performance when encountering an IS. In its core the ECT states that consumers form an expectation about a product prior to purchase. This expectation is mainly based on previous experiences and existing knowledge, such as, for instance, that gathered through contact with an agent (Zeithaml, Parasuraman, & Berry, 1990). In a second step, the actual performance[2] is compared to the prior expectation and creates an affective state (e.g. satisfaction or psychological tension). The resulting level of confirmation determines the degree of affection and the willingness to repurchase the product. The expectations further underlie a continuous change process, and are adjusted over time and transferred across different channels (Bhatnagar, Lurie, & Zeithaml, 2003). One can distinguish between pre-

[2] Apart from the ECT, our investigations consider the emergence of affect from a mere cognitive (mental) comparison of performance expectation and beliefs about the actual performance of the channel.

purchase expectations as those that are based on word-of-mouth, opinions or mass media and post-purchase expectations as those that result from prior purchases (Larsen et al., 2009). Both phases lead to different expectations through diverging abstractness in the imagination of product attributes. For the present research both phases are of relevance since the adoption of new channels by definition is based on abstract imaginations. The ECT has been applied in various fields of IS research to explain satisfaction and continuance usage (Brown, Venkatesh, & Goyal, 2012; Hossain & Quaddus, 2012; Larsen et al., 2009; Lin, Wu, & Tsai, 2005). Recently the theory gained in interest due to its potential to predict decisions in IS research (Hoehle, Scornavacca, & Huff, 2012). It has been integrated with other theories such as the theory of planned behavior and TAM (Hossain & Quaddus, 2012) but, to the author's knowledge, has not yet been applied to the confirmation of service performance and product complexity.

2.3.6 Status Quo Bias Theory.

Apart from an economical view of decision making through weighing costs against benefits, scholars repeatedly outlined anomalies in this behavior. Samuelson and Zeckhauser (1988) incorporated these anomalies in frame of the *status quo bias.* It delineates peoples' preference to maintain a given status or situation. To explain the status quo bias Samuelson and Zeckhauser (1988) distinguished three main mechanisms: Rational decision making, cognitive misperception, and psychological commitment:

Rational decision making results from the relative cost to benefit analysis (i.e. net benefits) of a certain change. The status quo bias occurs when the perceived costs exceed the benefits. According to Samuelson and Zeckhauser (1988) cost can be separated into *transition* and *uncertainty costs*. Transition costs occur whenever the switching costs exceed the efficiency gain retrieved by the superior alternative. Uncertainty costs arise when risks induce uncertainty in the decision process, for instance concerning the reliability of information that a channel provide. Thus, individuals stick with the current choice, as long as their demands are satisfied (Samuelson & Zeckhauser, 1988).

Cognitive misperceptions refer first to the overestimation of losses compared to gains in human decision behavior. Thaler (1980) named this the *endowment effect.* It fosters status quo inertia since switching costs are perceived to loom larger than switching gains. A second reason for misperceptions is *anchoring*, meaning the fact that for a status quo an imagination of how a service should look like exists. This provides a biased starting point for decision making and an information advantage for the existing solution.

Psychological commitment emerges by three mechanisms (Kim & Kankanhalli, 2009): First, s*unk costs* commit consumers to the status quo based on the desire to preserve prior resource investments by engaging in further such commitments (Samuelson & Zeckhauser, 1988). Second, Kahneman and Tversky (1982) found commitment due to *regret avoidance* that arises by higher feelings of regret for negative outcomes of new actions compared to negative outcomes through inaction. Third, commitment arises by the *drive for consistency.* This is formed by cognitive dissonance (Festinger, 1962) which captures humans' tendency to avoid the cognitive coexistence of conflicting ideas. It alters interpretation of information such that consistency is retained. The *self-perception theory* further theorizes that individuals infer their attitudes and preferences from past behavior (Samuelson & Zeckhauser, 1988) and rely on this behavior to make future decisions. Finally, commitment derives through the *illusion of control*. Langer (1983) demonstrated that the decision to keep the status quo accentuates consumers' illusion of control and thus induces change inertia. Falk et al. (2007) argue that among other theories, such as switching cost theory and inertia, the status quo bias theory is the best fitting model to explain channel choice behavior and is thus applied in this article.

2.3.7 Elaboration Likelihood Model.

The status quo bias theory and ECT fall short in explaining the psychological mechanisms that underlie the channel choice by omitting the cognitive processing of information. More appropriately, the ELM by Petty and Cacioppo (1986) differentiates information processing ("elaboration") for individuals with high and low motivation and ability. Ability hereto is determined by the underlying expertise (Bhattacherjee & Sanford, 2006) and thus proves relevance of the ELM in this research. Originating from motivation and ability the ELM postulates two distinct routes of persuasion. These are either the extensive consideration of issue-relevant information (central or systematic processing) or the peripheral consideration of informational cues (peripheral or heuristic processing). Consumers with high expertise are more likely to make a high cognitive effort and focus on central arguments such as complexity to form a choice (Park & Kim, 2009; Petty & Cacioppo, 1984). On the other hand, consumers with low expertise are more likely to utilize peripheral cues such as the channel popularity obtained through advertisements, commercial signals, and endorsements from IT experts or the amount of recommendations from peers. Decisions are therefore based on associations and rule of thumbs without considering issue-relevant arguments (Ho & Bodoff, 2014). The ELM gained great popularity in the past decades through its good construction, descriptive value for various situations, and high amount of citations (Kitchen, Kerr, Schultz, McColl, & Pals, 2014). Bhattacherjee and Sanford (2006) demonstrated the fit of the ELM in IS research by successfully incorporating the TAM. However, it is noteworthy that the replication of the model validity repeatedly failed (Cole, Ettenson, Reinke, & Schrader, 1990; Mongeau & Williams, 1996; Te'eni-Harari, Lampert, & Lehman-Wilzig, 2007) and raised questions about the appropriateness of the ELM for research on digital communication (Kitchen et al., 2014). However, IS research has confirmed the ELM use in understanding the persistence and changes in attitudinal behavior (Bhattacherjee & Sanford, 2006; Ho & Bodoff, 2014; Park & Kim, 2009; Yang et al., 2006) and thus justifies its usage in this research.

2.4 Research Model and Hypotheses Development

2.4.1 Complexity and ECT.

For complex products, expectation mainly evolves in two steps: First, by an appraisal of the product-related effort that has to be undertaken and second, by the assignment of the proper service performance to alleviate the effort to an acceptable amount. Service performance can be defined as the extent to which a service provider facilitates the purchase process of products and services (Zeithaml et al., 2002). These two steps generate a complexity-service expectation. The usage intention of a channel results when this complexity-service expectation matches the actual (or belief of) service performance in a specific channel. The resulting confirmation is referred to as complexity-service fit (CSF) in the following text. It corresponds to the service quality concept by Parasuraman, Zeithaml, and Berry (1985), which is derived from the comparison between what the consumer feels should be offered and what is actually provided. Scholars argue that higher product complexity is an antecedent to higher effort expectations (Loewenstein, 1999; Zhou & Lu, 2011). Further support for the CSF relationship comes from the UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003), which addresses the balancing of effort and performance expectations as predictor of behavioral intention. Based on these insights, we redefined and extended the ECT model as shown in Figure 2.1.

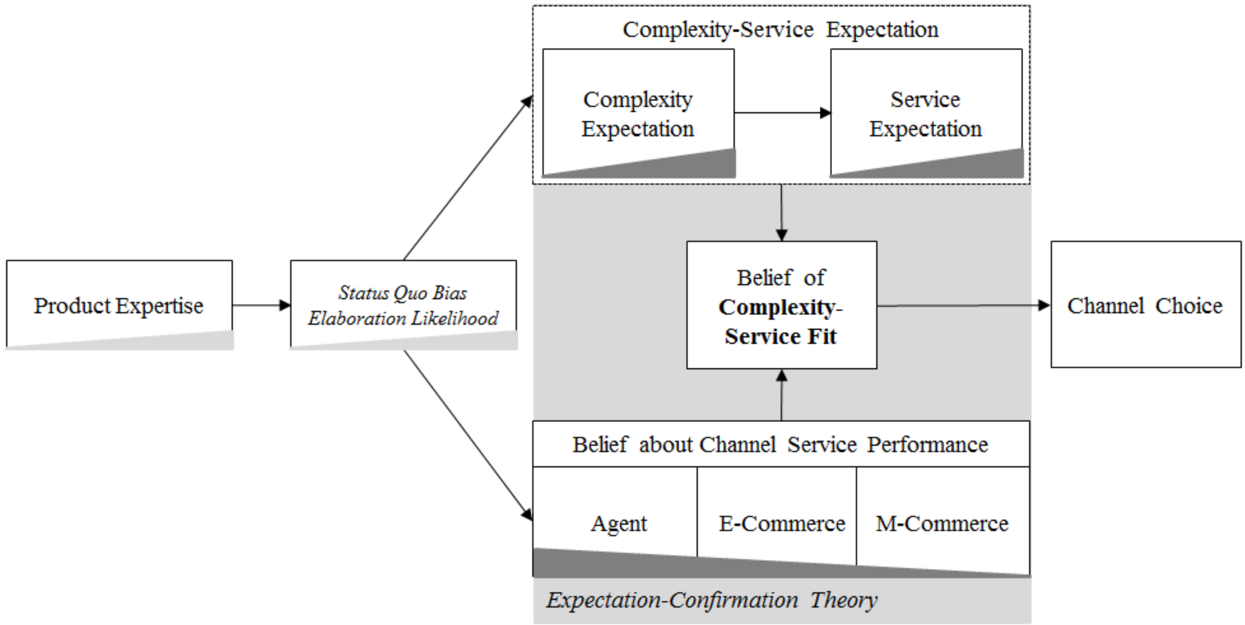

Figure 2.1 Integrated conceptual model to explain the mechanism of channel choice.Rising bars illustrate emerging relation: That is that product expertise reinforces the status quo bias and elaboration likelihood; Increasing complexity expectation causes a higher service expectations (or needs), which is opposing to the channel service performance trend, which is declining from agent to m-commerce.

Insurance agents usually reduce product complexity by providing consumers with extensive assistance (Swaminathan, 2003). Offline purchases therefore causes less expectation of self-effort, leading to high comfort (Selnes & Hansen, 2001) and a better CSF. Mayers and Smith Jr (1981) stressed that complex products substantially affect the level of service required by consumers. This increases the probability of relying on human services with higher complexity (Simon & Usunier, 2007; Wang, Harris, & Patterson, 2012). For the majority of complex products, online channels still lack sufficient service performance to substitute an offline consultancy (Ding, Verma, & Iqbal, 2007; Jin, 2012). This discrepancy is even stronger for mobile channels, since they provide a less comfortable handling (Lee & Benbasat, 2004; Zhou & Lu, 2011). The expected and actual CSF for complex products therefore falls apart, with highest confirmation for the agent (high service channel), moderate confirmation for e-commerce (medium service channel) and highest disconfirmation for m-commerce (low service channel).

Few studies have investigated the confirmation of channel service and complexity in IS research. Lin, Tsai, and Chiu (2009) found that service performance positively and service expectations negatively affect service confirmation. Wu and Griffin (2012) and Yang et al.

(2013) demonstrated that high service quality fosters a positive confirmation with expectations and enhances satisfaction and behavioral intention. However, Chiu, Hsu, Sun, Lin, and Sun (2005) found no support for the association of positive confirmation of service quality with satisfaction. Other studies suggest that channel choice is a matter of task fit, whereby higher complexity leads to less preference for low media richness channels and vice versa (Maity & Dass, 2014). Media richness thereby holds similar attributes as service performance; for instance, the availability of rich feedback, information and communication. Gefen and Pavlou (2012) investigated the perceived effectiveness of institutional structures (PEIS) and found that high PEIS hampers the willingness to transact. Drawing on the ECT this can be explained by a low CSF, due to the provision of high levels of service together with low product complexity. In fact, the authors investigated Amazon and Ebay, two platforms mainly offering low-complexity products compared to insurance. Conclusively, products with lower divergence (i.e. through higher standardization) require less service supply (Dumm & Hoyt, 2002). Low complexity is thus more likely to encourage consumers to use self-service technology such as m-commerce (Simon & Usunier, 2007; Wang et al., 2012). Medium and low complexity products are therefore most appropriate for medium and low service channels, respectively. The following hypotheses are stated:

> *H1: The purchase intention increases with higher levels of CSF. Agents generally achieve highest confirmation (main effect), followed by e-commerce and m-commerce.*
>
> *H2: The purchase intention of complex products per channel varies in dependence of the CSF, indicating an interaction of service performance with product complexity (interaction effect). The highest fit (purchase intention) per channel results for high service performance (agent) with high complexity, moderate service performance (e-commerce) with medium complexity and low service performance (m-commerce) with low complexity.*

2.4.2 Expertise, ECT and the Status Quo Bias.

A product encounter with an agent indirectly teaches consumers about the complexity of products; for instance, by imparting product specifics. According to the ECT, this gives consumers an indication about the effort that is needed when facing such a contract conclusion. Moreover, this allows them to form expectations about the performance that a service should supply in order to make a good decision. Bhatnagar et al. (2003) reported that consumers' experience in offline channels substantially influences their expectations for online services. Experienced consumers should consequently have a higher baseline of service expectations and complexity beliefs and be more extreme regarding their preference for agents and the declination of lower service channels. Experts may suspect less confirmation between their processing style and the new channels, especially for m-commerce, which exacerbates their resistance to adopt such channels (Park & Kim, 2009). For unexperienced consumers, the evaluation is a more abstract cognitive process, with less realistic beliefs, and results in less reliable outcomes about the CSF (Alba & Hutchinson, 1987; Swaminathan, 2003). The misfit of processing style and the channel characteristics should thus be lower.

This assumption is substantiated by the status quo bias theory, posing a stronger bias in favor of the agent for experienced consumers. This is because experiences with complex products are usually gathered in interaction with an agent (Dean, 2008; Heil et al., 2010; Jin, 2012). The status quo bias is defined by three mechanisms that generate channel retention as follows: For *rational decision making* in the presence of transition and uncertainty costs scholars (Burnham et al., 2003; Ziefle & Bay, 2005) found evidence that hesitance towards new technologies and switching costs grow the more complex this technology is. Evidence for this can be seen in consumers' widespread persistence with long-term contracts rather than switching to a better alternative. As a result of *cognitive misperception*, consumers are encouraged to preserve the investment (i.e. cognitive effort) that they have already made, in order to avoid sunk costs; for example, this can be scripts on how to manage an offline purchase. Thus, it is more likely that experts stick to the used channel than novices. Furthermore, prior experiences set-up an expectation of the required attributes of service, termed as an anchoring effect. Independent of its objective usefulness, this expectation defines the "must have" for new online services and is related to the expectation component in the ECT. However, online channels still lack comparable competencies such as flexible answering of complex questions. For *channel commitment* in the presence of regret avoidance, consumers with existing status quo will perceive stronger loss as a result of the reduction of service due to established routines. In line, Dean (2008) reported that older consumers with higher expertise miss human interaction more than younger consumers. The emerging search and evaluation costs for mobile insurance may further outweigh the benefits through self-execution such as time savings and control (Collier & Sherrell, 2010). More expertise thus leads to retain the channel status quo. Moreover, a self-induced poor product choice in consequence of using an online or mobile service will weigh more strongly than a third-party fault. Reasons can be the missing guarantee for self-induced failures or uncertainty about the consequences and ways of how to solve this situation. This intensifies the regret avoidance and encourages consumers to stick to common channels. By considering cognitive dissonance theory, a superiority of online channel attributes causes dissonance due to cognitive inconsistency. Higher expertise even reinforces these conflicting ideas. This may lead to a devaluation of benefits in the non-adapted channel. Dissonance also arises when negative confirmation (negative CSF) occurs (Anderson, 1973; Yang et al., 2013). This leads to psychological tension and uncertainty and therefore causes the avoidance of channels with low CSF expectation. Finally, self-perception regarding successful past transactions and the illusion of control for past decisions (Langer, 1983) will strengthen the motivation to keep the status quo, which is most likely the agent consultancy. Evidence for the status quo bias comes from the literature demonstrating that satisfaction with the offline channel reduces the willingness to use the online channel (Falk et al., 2007; Montoya-Weiss et al., 2003; Yang et al., 2013). Altogether this leads to the following assumption:

H3: The preference in a channel varies in dependence of the given level of product expertise, indicating a moderation of the effect of channel service on purchase intention by the product expertise.

H3a: Consumers with high perceived product expertise show a greater preference for the high service channel (agent) compared to consumers with low expertise.

H3b: Consumers with low perceived product expertise have a greater preference for the low service channel (m-commerce) compared to consumers with high expertise.

2.4.3 Complexity, Expertise and the Elaboration Likelihood Model.

As stated in the ELM, the central path requires higher levels of cognitive effort. Greater levels of expertise free up cognitive resources and make them available for a careful (systematic) processing of information (Alba & Hutchinson, 1987). High product experience allows an accurate representation of the genuine product and channel characteristics such as product variety. Furthermore, it enables consumers to select more efficient information to take good decisions. Greater knowledge also provides sufficient confidence to use complex information, and increases the tendency to defend initial attitudes by using counterarguments (Petty & Cacioppo, 1986; Tesser, 1978; Van Beuningen et al., 2009). Park and Kim (2009) demonstrated that consumers with high product expertise are more likely to value product attributes (i.e. insurance regulations or the limit of indemnity) to infer product benefits, while consumers with low expertise value information which expresses the benefit literally (i.e. medial reporting about the value of an insurance policy). Although an attribute-centric product approach confronts consumers with high complexity, it properly fits the cognitive processing of experts (Park & Kim, 2009). Novices lack comparable knowledge to draw such inferences. Persuasion is thus obtained from peripheral cues and heuristics. Positive messages (e.g. about ease of use and convenience of digital channels compared to low credibility of agents (Straughan & Lynn, 2002) may thus obtain greater weight for consumers with low expertise. They stronger consider new information to form their beliefs (Van Beuningen et al., 2009) and take a benefit-centric view. Detailed product information therefore appears meaningless for novices (Park & Kim, 2009). This suggests that individuals with low expertise are less likely to address complex product details in order to select a channel compared to consumers with high expertise. Bhattacherjee and Sanford (2006) reported that high expertise moderated the influence of central and peripheral cues on perceived usefulness. Higher expertise values led to higher influence of central cues and less influence of peripheral cues. Central arguments such as policy details should increase in influence for experienced consumers. Yang et al. (2006) found that product information quality weighs more strongly for consumers with high involvement (high motivation) due to central processing of information. Finally, Jaiswal, Niraj, and Venugopal (2010) reported higher influence of ease of use on satisfaction, when web expertise was high. This leads to the following assumption:

> *H4: The influence of complexity on risk perception is moderated by the level of product expertise a consumer holds. High levels of expertise lead to higher influence of complexity on risk perception, while lower levels lead to lower influence of complexity on risk perception.*

2.5 Research Methodology

2.5.1 Design and Procedure.

An online survey was conducted to evaluate the hypothesized relations. To test the stated hypotheses, we chose a set of four common insurance policies as the basis of assessment. The selection was derived by an online market research project concerning the suitability of e-business and insurance (Holzheu, Trauth, & Birkmaier, 2000) under consideration of different levels of product complexity. Accordingly, we grouped these products into three complexity categories. These are low complexity consisting of either travel insurance or car insurance, high complexity consisting of either health insurance or life insurance. Additionally, we build a third low complexity group, with insurance policies that were new to the market and thus were less well-known. This category was determined by either electronic device insurance or sports equipment insurance. We expected this category to be the lowest in complexity assessment since its representation should have been less concrete (e.g. fewer details in mind) (Alba & Hutchinson, 1987). In total our study consisted of six insurance policies. To establish a common understanding, all insurance policies were introduced by a short introduction text.

The questions were designed in a forced-decision format; hence there were no missing values in the data set. The data screening revealed no invalid responses, thus all answers were included in the evaluation. All respondents had the chance to take part in a lottery, offering the chance to win one of two amazon vouchers to the value of €50. Prior to the evaluation, we tested the survey with 20 students in order to address issues regarding the comprehension of questions. These testers initially answered the questionnaire and were interviewed afterwards about remaining ambiguities. We further verified our selection by conducting an online pre-test under inclusion of 27 insurance consumers and agents. The task was to place several insurance policies in order of product complexity as defined in this article. This test confirmed the chosen order of complexity for our products. Finally, in the course of the questionnaire the respondents were asked to assess each insurance policy. Therefore, the participants were randomly assigned to one of each insurance category – new, low and high complexity. Each category eventually contained 329 assessments. Subsequently, the remaining constructs such as risk and purchase intention were evaluated.

2.5.2 Sample.

In total, 329 respondents participated in the study[3]. These were recruited by distributing the survey link to social networks, blogs, forums and websites. The evaluation took place from October 2013 to January 2014.The participants were aged between 16 and 70 with a mean of M = 29.06 (SD = 7.82). The gender was quite balanced, with 53.5% women and 46.5 % men (SD = 0.50). The education level was dominated by high school graduates (55.3%), followed by secondary education (33.7%), middle secondary (9.4%) and lower secondary education (0.9%). At least 0.6% had no schooling. The participants' monthly income was distributed as follows: 36.2% received €1,000 or less, while 18.8 % had an income between €1,001 and

[3] The data evaluation of this study was partly conducted together with Nils Niederkleine in context of his master thesis, which was supervised by me.

€2,000, followed by 16.1 % with a higher income than €2,001 but lower than €3,000. Finally, about 29% earned more than €3,001. A detailed overview of the demographics can be seen on Table 2.1.

Table 2.1 *Profile of Respondents.*

Measure	Item	Frequency	Percentage (%)
Total		329	100
Gender	Male	153	46.5
	Female	176	53.5
Age	Below 20	9	2.7
	20-29	211	64.1
	30-39	84	25.5
	Over 40	25	7.6
Education	No schooling completed	2	0.6
	Lower secondary school	3	0.9
	Middle secondary school	31	9.4
	Higher secondary school	111	33.7
	Graduates	182	55.3
Income in €	< 1000	119	36.2
	1001-2001	62	18.8
	2001 - 3000	53	16.1
	3001 - 4000	50	15.2
	4001 - 5000	25	7.6
	> 5000	20	6.1
Online Insurance Usage	Yes	119	36.4
	No	208	63.2
Smartphone Ownership	Yes	270	82.1
	No	47	14.3
Knowledge about Mobile	Yes	71	21.6
Insurance	No	255	77.5

2.5.3 Measures.

The principle constructs were analyzed by applying existing measures which were partly adapted to the specific context of the study. All items were rated on a 1-7 Likert-type scale, with a value of one for strongly disagree up to seven for strongly agree. Perceived product complexity was assessed by taking three items of the service complexity scale published by Burnham et al. (2003). The scale revealed an acceptable Cronbach´s Alpha of .81 consistent to the reported values by Burnham et al. (2003). To measure risk perception, we took three items for psychological risk as proposed by Crespo, del Bosque, and de los Salmones Sánchez (2009). Cronbach's Alpha lay slightly above (α = .96) the values reported by Crespo et al. (2009). Insurance expertise was measured by using items from Novak, Hoffman, and Yung (2000) as applied by Jaiswal et al. (2010). The Cronbach´s alpha for insurance expertise slightly exceeded the previous reported values. For purchase intention we eventually used two items by Burton and Andrews (1996) in an adapted version of Gupta et al. (2004a). The scale revealed a Cronbach´s Alpha of .94 and is in line with findings of Gupta et al. (2004a). All items are reported in the Appendix 8.1.

2.5.4 Model Fit.

To verify the construct validity, the multi-item scales were screened by an exploratory factor analysis (EFA). The EFA revealed five factors with an eigenvalue above 1 which explained 81.5% of the overall variance among all items. All items revealed high loadings in correspondence to their related factor, which ranged between .76 and .97 and exceeded given recommendations of .70 (Hair, Black, Babin, & Anderson, 2013). We also controlled the construct validity by testing the average variance extracted (AVE) values as indicator for convergent validity and the square-root of the AVE known as Fornell-Larcker criterion (Fornell & Larcker, 1981) as indicator for discriminant validity. All AVE values exceeded the threshold of .50. The square-root of the AVE was higher than all related inter-variable correlations. A subsequent confirmatory factor analysis (CFA) revealed a good model fit ($\Delta\chi^2 = 2.21$, CFI = .97, RMSEA = .061). Thus the data were adequate for further investigations. A summary of all test results is given in Table 2.2 and Table 2.3 together with descriptive statistics and correlations.

2.5.5 Common Method Bias.

Finally, we controlled our data for a common method bias (CMB) as suggested by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). Two procedures are primarily recommended in the literature: First, the conduction of a Single Harman's Factor Test (Harman, 1976) and second the Marker Variable Technique (Lindell & Whitney, 2001; Podsakoff et al., 2003). The first suggests that a common method bias is prevalent, when more than 50% of the variance in all items can be explained by one single factor. Our testing revealed a common variance of 33.6% and therefore did not exceed this threshold. Second, we built a measurement model where all items loaded on one single factor next to their corresponding factor. To isolate the common method variance we integrated an apparently non-correlated marker variable and used four items of affective involvement. The test revealed a non-critical common method variance of 4.8%. In conclusion, we found no support for a CMB in our data.

Table 2.2 *Test Results of Internal Reliability, Convergent Validity and Exploratory Factor Analysis.*

Construct	Items	Cronbach's α	AVE	Item-total correlation	EFA				Author
Complexity	3	.81	.62	.71	.82				(Burnham et al., 2003)
				.53	.83				
			.88	.75	.82				
Psychological Risk	3	.96		.89		.92			(Crespo et al., 2009)
				.94		.94			
				.89		.93			
Insurance Expertise	4	.94	.78	.83			.90		(Novak et al., 2000)
				.88			.94		
				.85			.92		
				.87			.93		
Purchase Intention	2	.94	.88	.89				.96	(Gupta et al., 2004a)
				.89				.97	

Table 2.3 *Correlations and Discriminant Validity.*

	M	*SD*	1	2	3	4	5	6	7
1 Complexity	4.24	1.11	**.79**						
2 Psychological Risk	3.07	1.27	.54**	**.94**					
3 Product Expertise	3.19	1.54	-.10	-.07	**.89**				
4 Purchase Intention	3.46	0.95	-.16**	-.19**	.10	**.94**			
5 Age	29.06	7.82	.15**	.08	.24**	-.15*	-		
6 Gender	1.47	0.50	-.02	.00	.22**	.12*	.03	-	
7 Education	4.42	0.75	-.19**	-.13*	.01	.18**	.03	-.01	-
8 Income	2.57	1.57	-.11	-.10	.34**	.10	.42**	.14**	.23**

Notes. Diagonal entries (bold) are the square root of the average variance extracted (AVE). ***p* < .01 (one-tailed). **p* > .05 level (one-tailed).

2.5.6 Manipulation Check.

We controlled whether the selected insurance policy differed in the level of complexity in order to validate the disparity of the conditions for the independent variable. The comparison of all three categories applying pairwise comparisons confirmed a significant difference between medium and high as well as low and high complexity. Though in the right direction, no significant difference was found for the categories low and medium complexity ($\Delta M_{low\text{-}high}$ = -0.95, SE = 0.08, $p < .001$; $\Delta M_{medium\text{-}high}$ = -0.80, SE = 0.08, $p < .001$; $\Delta M_{low\text{-}medium}$ = -0.15, SE = 0.07, *n.s.*). The group differences nonetheless support the proceeding of analysis due to the correct order of deviations between all three conditions.

2.6 Results

Several tests were applied to examine the assumptions. At first, by using an ANOVA, the influence of different levels of experience on channel choice was tested. A subsequent stepwise regression was applied to test for the hypothesized interaction effect. Polynomial regression modeling and the response surface method (RSM) were eventually used to estimate the alternation for the effect of complexity on risk in dependence of the amount of experience. The evaluation of the hypotheses was undertaken by using IBM SPSS® 21 and Matlab® 2015b.

2.6.1 ANOVA and Regression.

Prior to the ANOVA, we tested the sphericity of the data by using Mauchly's Test. The result obtained a significant result, which suggests the usage of a correction method in the course of the ANOVA (two-factorial with repeated measures). The reported statistics are therefore based on the Greenhouse-Geisser corrected values.

In accordance with hypothesis H1, a significant main effect for the service performance was found ($F(2, 656) = 273.10$, $p < .001$, $\eta^2 = .45$, Power = 1.00). This means that the agent is the preferred channel throughout all conditions of complexity. Further analysis using the Bonferroni post-hoc test confirmed a significant difference in the predicted direction ($\Delta M_{Agent\text{-}PC} = 1.03$, $p < .05$; $\Delta M_{Agent\text{-}Mobile} = 2.70$, $p < .05$).

In support of hypothesis H2 there is a significant interaction of large effect size between the factors complexity and channel service ($F(3.38, 1110) = 103.51$, $p < .001$, $\eta^2 = .24$, Power = 1.00). Thus, the purchase intention for the considered channels varies in dependence of the level of complexity. While the preference for agents increases along with the level of complexity, the preference for mobile purchases reveals a reversed trend. To specify these effects, we conducted several post-hoc contrasts to evaluate the significance for the preference differences within each channel as stated in Hypothesis H2. In line with H2, for agents the products with high complexity reveal the highest purchase intention, while products with low complexity reveal the lowest purchase intention ($F(1,984) = 66.00$, $p < .001$, $\eta^2 = .063$; Contrast weights low, medium, high = -2 -1 3). As further posed in H2, for m-commerce the products with low complexity reveal the highest purchase intention, while products with high complexity render the lowest purchase intention ($F(1,984) = 19.01$, $p < .001$, $\eta^2 = .019$; Contrast weights low, medium, high = 3 -1 -2). Therefore, e-commerce obtains the highest purchase intention for the medium levels of complexity ($F(1,984) = 30.87$, $p < .001$, $\eta^2 = .03$; Contrast weights low, medium, high = -1 2 -1).

In Hypothesis H3 we posited a significant moderation effect of channel service on purchase intention through product expertise. Therefore, the sample was split into two groups according to the upper and lower 50% of expertise. In support of H3 there was a significant moderation of small effect size ($F(2, 981) = 3.81$, $p < .05$, $\eta^2 = .008$, Power = .69). Although consumers with high product expertise showed a higher propensity towards the agent as buying channel compared to consumers with low expertise, the effect of the direct comparison was not significant ($t(985) = 1.61$, $p = .11$). However, in support of hypothesis H3b, consumers with low expertise revealed significant higher purchase intention for e-commerce ($t(985) = -2.05$, $p < .05$) and m-commerce compared to consumers with high expertise ($t(939) = -4.52$, $p < .001$). This indicates that consumers with high experience are more extreme in their preferences, while consumers with low expertise reveal less declination of the digital channels and thus show higher indifference regarding the channel selection. The results for both interactions are illustrated in Figure 2.2.

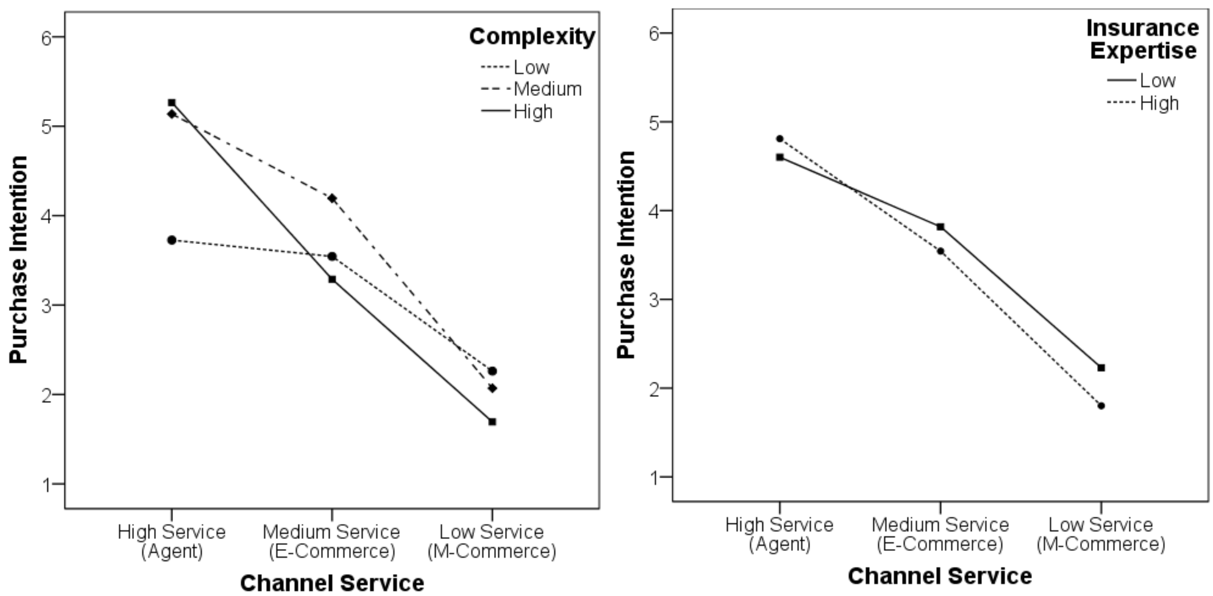

Figure 2.2 Interaction effects of complexity and expertise with channel service.

2.6.2 Polynomial Equation Modeling.

As postulated in H4, the effect of complexity on risk is moderated by the level of expertise. To test the hypothesis, we conducted a confirmatory polynomial regression analysis. The procedure has recently attracted interest due to criticism of the oversimplified concatenation of variables and encourages an investigation of higher order relations (Brown et al., 2012;

Edwards, 2002; Gefen & Pavlou, 2012; Venkatesh & Goyal, 2010). In the case of complex products we consider two types of moderation as plausible. This is a linear first-order interaction or a non-linear quadratic interaction. The latter means that the influence of complexity increases the more expertise available, constituting a quadratic moderation through expertise. As previously mentioned, one reason can be seen in the growing self-confidence and ability to integrate complex information into the decision with higher levels of expertise (Meuter et al., 2005). Therefore, both cases are tested here in an exploratory fashion. The following equation is concluded:

$$Z_{PI} = a_0 + b_1 X_{Comp} + b_2 Y_{Exp} + b_3 (X_{Comp} * Y_{Exp}) + b_4 Y_{Exp}^2 + b_5 (X_{Comp} * Y_{Exp}^2) + b_i + \varepsilon_0$$

Equation 1

Prior to the analysis, we examined the practical relevancy of this model by testing if psychological risk in fact mediates the association of complexity and purchase intention. By applying the Bias-Corrected Bootstrap Method in frame of a structural equation model (Cheung & Lau, 2008; Lau & Cheung, 2012; MacKinnon, Lockwood, & Williams, 2004) a full mediation through psychological risk was supported (β = -.06, p = .32). We found a significant indirect negative effect for complexity on purchase intention (β = -.85, *CI90*[.16,-.03], $p < .01$). The relevancy of the model was thus supported.

As shown in Table 2.4, the regression was composed of five steps: First, the control variables were introduced followed by the linear terms in the second step. The third and fourth steps included the interaction term and the quadratic term, respectively. Lastly, the third order interaction term (quadratic moderation) was introduced. All IV were z-standardized prior to the analysis to reduce multi-collinearity issues and facilitate interpretation (Dawson, 2014). For control variables we used key confounding variables such as age, gender, education and income (Gefen & Pavlou, 2012; Venkatesh & Morris, 2000).

The results supported a significant negative effect of complexity on psychological risk (β = .42, $p < .001$). The linear model in step 2 explained 19.3% of variance in psychological risk and therefore explained 16.7% beyond the control variables. Expertise revealed no significant linear effect or a quadratic effect on psychological risk (β = -.05, p = .37; β = -.02, p = .77). Also there was no significant linear interaction between complexity and expertise (β = .08, p = .13). However, the quadratic moderation was significant (β = -.17, $p < .05$)[4]. The

[4] Edwards (2002) suggested including all higher order terms in the regression until no incremental variance is explained. We thus also tested the 4. order moderation effect in a subsequent step by adding Y_{Exp}^3 and $X_{Comp} * Y_{Exp}^3$ to the regression. However, consistent to our assumptions neither term explained a significant increment of variance.

cubic model in step 5 explained a further 1.1% of variance in psychological risk above the linear model (step 2) and revealed a significant F-change. The effect was of medium effect size ($f^2 = .138$)[5]. In total, the model explained 20.4 % of variance in perceived psychological risk. The results support an increasing impact of complexity on risk when product expertise is rising. This is further specified by the RSM (Edwards, 2002).

2.6.3 Response Surface Methodology.

As shown in Figure 2.3, the function revealed a slope of 27.95° degree for low expertise (point 1), a slope of 21.70° degree for medium expertise (point 2) and a slope of 49.2° degree for high expertise (point 3). We thus found support for the predicted relation, although the obtained inverted saddle shape slightly deviates from the predicted lowest influence of complexity for Y = -3. The lowest impact was found at Y = -1.55 corresponding to "rather no expertise" to "no expertise", with a slope of 18.92° degree. In conclusion our data obtained partial support for hypothesis H4.

Table 2.4 *Results of the Polynomial Regression Analysis.*

Effects	Step 1 Controls	Step 2 Linear	Step 3 Interaction	Step 4 Quadratic	Step 5 Cubic
Age	**.14***	.07	.07	.07	.07
Gender	.01	.02	.02	.02	.01
Education	-.11	-.04	-.05	-.05	-.04
Income	**-.13***	-.05	-.05	-.05	-.05
Complexity		**.42****	**.41****	**.41****	**.30****
Expertise		-.05	-.05	-.04	-.03
Complexity * Expertise			.08	.07	.03
Expertise²				-.02	-.01
Complexity * Expertise²					**.17***
Adjusted R²	.026	.193	.196	.194	.204
ΔF(Δdf)	3.2(4)*	34.4(2)**	2.4(1)	0.1(1)	5.1(1)*

Notes. Independent Variable = Psychological Risk. The numbers in bold highlight significant effects.

A further specification of the response surface concretized the inverted effect of expertise on risk perceptions. For products with low complexity such as the afore-mentioned electronic device insurance, increasing expertise diminishes the risk perceptions (above the value of $Y_{Exp} = -1.13$ (local maximum) with $X_{Coplx} = -3$). Conversely, expertise fuels the perception of psychological risk for products with high complexity such as life insurance (above the value of $Y_{Exp} = -0.97$ (local minimum) with $X_{Coplx} = 3$).

[5] We referred to the effect sizes as derived by (Aguinis, Beaty, Boik, & Pierce, 2005) 30-year review of literature and proposed by Kenny (Kenny, 2015). According to that, values of .005 correspond to small effect sizes, values of .01 correspond to medium effect sizes and values of .025 correspond to large effect sizes

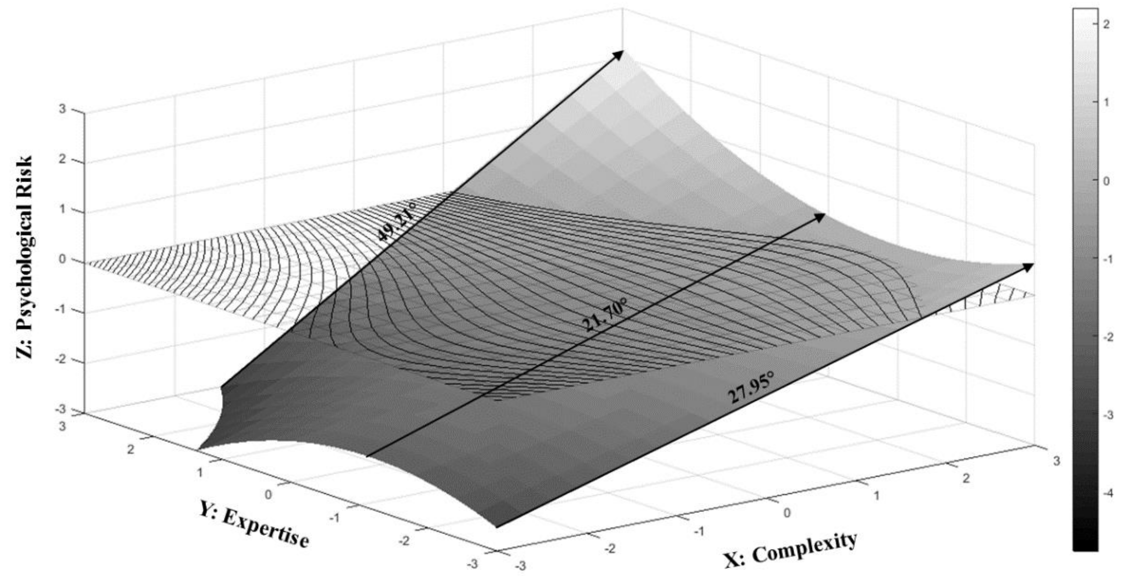

Figure 2.3 Response surface for the quadratic moderation. The graph shows the effect of complexity on psychological risk moderated through expertise. Black arrows depict the effect of complexity at different levels of expertise in degree. The layer at z = 0 illustrates the transition from risk perception to no risk perception.

2.7 Discussion

The focus of this study was to explore mechanisms that affect channel maintenance behavior in multi-channel environments for complex products. An integration of three common theories, the expectation-confirmation theory, the status quo bias theory and the elaboration likelihood model was conducted to gain an in-depth understanding of channel choice.

The research obtained three main findings: Firstly, the results confirm the meaning of complexity for channel choice behavior, as a key determinant to the expectation-confirmation ratio in the ECT, denoted as complexity-service fit (CSF) in this article. A significant main effect for channel service confirmed that higher complexity increases performance expectations and accordingly increases the preference for high service channels. In consequence, the agent was the most desired product encounter for complex products, followed by medium and low channel service. The resulting hesitance to adopt new channels such as e- and m-commerce thus results from the decrease in CSF. In a second analysis it was shown that when considering each channel separately, the highest purchase intention results for high product complexity with high channel service, for medium complexity with medium channel service and for low complexity with low channel service, supporting the need for CSF.

Secondly, product expertise reinforces channel maintenance behavior. This assumption was theoretical underpinned by incorporating the status quo bias theory next to the ECT. A significant interaction effect provided support that consumers with higher product expertise have stronger ties to the high service channel and less preference for competing channels. Consumers with lower expertise on the contrary revealed less stringency regarding the respective channels. This suggests a higher indifference in the channel choice for low experienced consumers.

Thirdly, the impact of complexity on the perception of risks varies in dependence of the level of product expertise that a consumer holds. An investigation of the response surface of the polynomial regression showed that complexity has a greater impact on the purchase decision for individuals with high product expertise compared to medium and low expertise. A further specification outlined a quadratic moderation, meaning that expertise lowers psychological risk when complexity is low, but intensifies psychological risk when complexity is high.

2.7.1 Theoretical Implications.

The present study advances IS literature by introducing established theories to multi-channel research. This fortifies the literature in several ways: First, the article exploits and confirms the potential of the ECT to further explain channel selection behavior as demanded in the literature (Hoehle et al., 2012). We augmented the ECT by including complexity and expertise as antecedents of the expectation-confirmation emergence and by proposing the complexity-service fit as a key predictor for channel choice. The integration of these factors enhances previous findings that had already stated a positive influence of confirmation on channel acceptance, but failed to identify the key factors for the emergence of expectation-confirmation (Brown et al., 2012; Chiu et al., 2005; Wu & Griffin, 2012; Yang et al., 2013). This advances research regarding the understanding of channel extension and maintenance by providing a more comprehensive basis for future investigations.

Secondly, our research synthesized the status quo bias theory and ELM in order to enrich the understanding of the effect of complexity and expertise. This synthesis is new in IS research and was useful for the following reason: While the status quo bias theory provides several reasons that determine channel maintenance it lacks elaboration on the psychological mechanisms that underlie decision making. The ELM compensates for this deficit by taking divergent selection, processing, and evaluation of information into account. Although there is some overlap (e.g. for the anchoring effect), the different processing routes in dependence of a consumer's expertise in the ELM substantiate the status quo bias theory. The obtained underpinning allows us to better account for interactions in multi-channel research with regard to expertise. The synthesis further allowed investigating the reasons that are fundamental to channel maintenance behavior in complementation to the dominating body of literature about the positive antecedents of channel extension (Bhattacherjee & Sanford, 2006; Maity & Dass, 2014).

Thirdly, the proposed higher order model sheds new light on the effect of complexity on channel choice behavior by allowing for moderations. It substantiates the role of experience as a moderator with antecedents of technology adoption (Nysveen & Pedersen, 2004; Venkatesh & Davis, 2000). While scholars argued that an information overload persistently hampers the adoption of new channels, our results limit this stance to a matter of prior expertise. Frustration therefore occurs when information contradictory to the processing style is presented, such as attribute-centric information for novices and benefit-centric information for experts. Our results further limit the sphere of influence that complexity has as a determinant of expertise and processing style. This corresponds to prior incongruences about the interaction of task complexity and channel preferences (Maity & Dass, 2014; Simon & Usunier, 2007). In contrast to model assumptions by Muthitcharoen et al. (2011), our data support detailed investigations by experienced consumers and usage of peripheral cues for non-experienced consumers.

Lastly, our results help to explain anomalies in the effect of expertise on channel choice. While the majority of literature highlighted advantages of internet experience in adapting a digital channel (Falk et al., 2007; Forsythe & Shi, 2003; Gordon & Anand, 2000; Jaiswal et al., 2010), we found contradicting results for product expertise. Our findings suggest that internet expertise is associated with less status quo bias tied to the offline channel compared to product expertise (for complex products). In line, Falk et al. (2007) showed that internet experience lowers the resistance to adopt an online channel, despite existing offline channel satisfaction. Conclusively, both product expertise and internet expertise provide specific skills to enter a digital channel more easily, but lead to opposed motivation to ultimately do it. This emphasizes the need to distinguish the source of expertise and status quo in future research.

2.7.2 Practical Implications.

The interplay of complexity and expertise yields numerous implications for the future management of complex products. Firstly, complexity was found to stipulate the level of service implementation. The amount of service for mobile-based insurance policies should thus be increased to reduce uncertainty. Five dimensions have been identified as useful orientation for a high level of service, namely reliability, responsiveness, empathy, assurance, and tangibles (Zeithaml et al., 1990). To satisfy these dimensions scholars suggest the implementation of media richness, containing feedback, communication possibilities, personal focus and language variety (Maity & Dass, 2014). On the product side, the results propose a strong facilitation of the product to easily understand its details. This can be achieved by improving the comprehension, for instance by avoiding technical jargon or prolix policies. Instead product designers should be eager to provide hierarchical structured information; for example, by showing summarized product information on the main page, as well as detailed background knowledge in the second level (e.g. behind toggle bars). This allows consumers to control the depth of product exploration, and also provides sufficient information to make a confident decision after having seen the main pages.

Furthermore, expertise was shown to hamper channel extension. A successful multi-channel strategy therefore requires mitigating the status quo bias. Expertise should accordingly be made compatible and shifted towards innovative channels. This can be accomplished by connecting in-store experiences with mobile advantages. For instance, the app Shopkick provides the possibility to obtain discounts in numerous stores by entering the sales room with the app activated. In addition, the scanning of products instore and receiving supplementary information on a smartphone (e.g. product reviews), as well as self-check-out opportunities, could reduce the pitfalls of offline channels. This would enable a flexible exploration derived through the confluence of in-store and online consultancy, and the purchase in either channel. Conversely, online channels could be equipped by human components, such as telephone hotlines, chats, email functions, avatars or chatbots (Froehle, 2006) to simulate human capabilities for online channels. Another approach is the complement designing of channels, by providing only partial service across channels (Falk et al., 2007) to create a positive state of channel entitativity (Yang, Lu, Zhao, & Gupta, 2011). Dell, for example, offers advice, support and “touch and feel” in local stores, but does not support the ordering of a product in these stores. Although this strategy may hold some advantages, it restricts the flexible choice of consumers with different preferences. In addition to the proposed means consumers can be taught about other channels; for example, by providing tutorials and incentives to allow free trials. Channels should also be compatible with prior knowledge by using the same technical language or procedure established from previous human encounters. This relaxes the transition, uncertainty and sunk costs. Guaranties can further help to prevent both loss aversions and regret avoidance.

Finally, it was shown that different levels of expertise stimulate divergent processing. Marketing should thus approach consumers with different experience according to their preferences of cognitive processing. Therefore, consumers with high expertise should be well provided with detailed information all around the product. This information should target the central rather than peripheral attributes of the product. Such information could be policy details, limits of indemnity, statistics or pricing models. However, it is noteworthy that irrelevant information can cause frustration and uncertainty (Hausman & Siekpe, 2009; Yang et al., 2006) and should thus be avoided. Conversely, consumers with low expertise should rather be provided with benefit-centric information. Park and Kim (2009) suggest standardizing reviews such that each review contains both benefit-centric and attribute-centric information and establishes a general fit for both preferences. In addition to reviews, campaigns such as placing advertisements in social networks, supporting opinion leaders, referring to testimonials and experts, implementing trust-seals etc. can help to persuade novices to use digital channels. Altogether, marketers should invest in the personalization of the product presentation consistent to the respective expertise of the consumer.

2.7.3 Limitations and Future Research.

The presented results have some limitations and suggest future research in several aspects. We synthesized three essential theories from IS and marketing research. Nevertheless, there are concurring theories which hold further insights for the understanding of the mentioned processes. In this context the switching cost theory, inertia (Falk et al., 2007), the continuity theory (Dean, 2008), the cognitive fit theory (Park & Kim, 2009) and the resource matching theory (Collier & Kimes, 2012) are of relevance. The resource matching theory, for instance, theorizes that adoption of self-service technologies depends on the perceived matching between required and available resources (i.e. time). Since internet expertise revealed positive associations to channel extension contrary to product expertise, it might be presumed that internet expertise is the more essential resource for channel extension. Future studies should thus integrate concurring theories to gain a deeper understanding of the effect of different types of experience.

Like other studies before (Falk et al., 2007; Forsythe & Shi, 2003; Simon & Usunier, 2007), we investigated complex products for one product class but disregarded a holistic classification in categories such as search, experience and credence goods. Research revealed mixed effects for different channel preferences with regard to different product classes (Maity & Dass, 2014; Simon & Usunier, 2007). In this context is might be argued that expertise with financial services such as insurance, online banking or mortgages increases in importance with increasing age and is thus positively related to age, and consequently causes higher need for interaction and lower internet experience (Dean, 2008). Other complex products such as travel have reached far more popularity in online commerce. However, travel, is important consistently across different age groups and thus does not provoke negative associations for product expertise with internet expertise. The argumentation that high product expertise leads to higher complexity consideration may not hold true for every product class. Although we controlled for age and picked a relevant age group (Walczuch & Lundgren, 2004) future studies should allow for this circumstance.

Recent theorizing by Gefen and Pavlou (2012) shed further light on the association of complexity and risk. The authors argue that low perceived institutional effectiveness reduces the effect of perceived risk on purchase intention. This limits our assumption in terms of another interpretation of our results. Complexity may exceed the level of competence for low-experienced consumers. In consequence, vulnerability surpasses the tolerated range and leads to low interest in the product instead of low influence of complexity through divergent processing. This aspect should be targeted in future studies such as by controlling for interest in the product and feelings of vulnerability.

Finally, the difference in processing could also be an argument for channel extension equally to the ROPO behavior. A high need for detailed, effortful processing as found for experienced consumers could thus be argued to reinforce the online channel usage, since internet provides the appropriate variety of information. However, we did not address the research antecedent to purchasing, but the purchase itself. Future engagement should therefore consider the use of online mediums in different phases of the decision process.

2.8 Conclusion

In this article we investigated the influence of service complexity on channel choice behavior under taking account for consumer expertise with the product. Referring to three fundamental theories, the expectation-confirmation theory, the status quo bias theory and the elaboration likelihood model, we demonstrated that each of the two variables is positively associated to channel maintenance. Moreover, complexity is of higher relevance for experienced consumers, since they strive for a detailed product encounter. This outcome suggests a clear differentiation between product and channel expertise and explains anomalies in multichannel research that revealed mixed results regarding the role of expertise for channel choice. The extension and synthesis of the afore-mentioned theories transfer their potential to multichannel research and reveals new insights. From a practical perspective this increases knowledge about the information and service level that is required to satisfy experts and novices in various channels. Product managers need to level service performance across channels in order to convince consumers with existing expertise to change their channel attitudes. In addition, products need to be adjusted to the according distribution channel concerning their complexity. If this conversion can be mastered, multi-channel sales will provide a convenient product encounter at consumers' option.

STUDY 2

3 Ladders to M-Commerce Resistance: A Qualitative Means-End Approach

3.1 Abstract

Although mobile commerce is predicted to be the next megatrend with steadily increasing buyer rates, some industries are struggling to adopt this trend and face strong consumer resistance. This particularly concerns complex, service based products such as insurance. The long sales tradition in this area, with a network of agents, brokers and bank advisors, has caused a perceived divergence between the characteristics of the established and the emerging channels. This article aims to identify the sources of resistance to mobile insurance by uncovering the relationship between the values of consumers and the conflicting attributes of the mobile channel. Therefore, insurance consumers with existing knowledge about mobile insurance, but inherent resistance were interviewed. A laddering interviewing technique was used to retrieve chains of attribute, consequence and value relations. This provides a profound understanding of the consumers' cognitions by mapping and structuring the sources of resistance. The results mainly highlight an insufficiency of the service, and system components as key barriers to adoption. Theoretical and practical implications are discussed.

3.2 Introduction

The rise of mobile devices has taken the world by a storm. Mobile commerce enables an "anywhere, anytime" culture and customized connectivity to services, and enhances the convenience of shopping (Coursaris & Kim, 2011; Ozok & Wei, 2010). Mobile commerce is predicted to account for 36.5% and 30.1% of online sales in 2016 for the U.S. and Europe respectively. The growth rate of the transaction volume for mobile devices will be 187.7% compared to 9.9% for PCs and laptops from 2014 to 2016 for Europe (Centre of Retail Research, 2015). However, this trend reaches its limit for complex products that are commonly related to human interaction such as insurance (Devlin, 2007). Drawing on a recent evaluation among smartphone owners, the usage of mobile retail was four times as much as for mobile insurance, which was ranked among the least attractive businesses in m-commerce (Statista, 2013), even though it provides a number of advantages, such as ubiquity, convenience, localization, instant connectivity and personalization (see Cao et al., 2014).

Despite the growing impact of m-commerce, few studies have investigated the reasons that prevent consumers from entering mobile commerce (Liébana-Cabanillas, Sánchez-Fernández, & Muñoz-Leiva, 2014; Zhou & Lu, 2011). Moreover, research was mainly devoted to abstract intermediaries and end-values of m-commerce acceptance as for instance theorized in the technology acceptance model (TAM; Al-Debei & Al-Lozi, 2014; Jeong & Yoon, 2013; Negahban & Chung, 2014) and related constructs (Phan & Daim, 2011). This neglects the key determining psychological mechanisms that inhibit its diffusion. In a meta-analysis Coursaris and Kim (2011) generally note a lack of studies that incorporate concrete usability issues and the total absence of qualitative studies in this area. An investigation about the evolvement of resistance in m-commerce is therefore of high relevance for theory and practice (Al-Debei & Al-Lozi, 2014; Cao et al., 2014; Hausman & Siekpe, 2009; Negahban, 2012; Negahban & Chung, 2014). This article aims to fill the gaps through analyzation of the resistance towards m-commerce for complex products by focusing on the bottom-to-top emergence of barriers towards channel extension. In this frame, the means-end approach based on laddering interviews has proven its usefulness (Kuisma et al., 2007; Reynolds & Gutman, 1988). This approach proposes a hierarchical structure capturing inherent service attributes ("means"), thereof resulting consequences for consumers and personal values ("ends") reinforced by the consequences (Reynolds & Gutman, 1988).

The present article advances theory in different ways: Firstly, with regard to the means-end hierarchy, previous investigations have been predominantly limited to the scope of abstract consequences and values in direct relation to technology adoption, but disregard the antecedent attributes. We extend this scope by uncovering attribute-value linkages in order to allow an in-depth understanding of the hesitance to adopt mobile channels, with particular meaning for complex products. This is consistent with previous demands from literature (e.g. Kuisma et al., 2007).

Secondly, today's research on consumer resistance is often based on past concepts which need to be adjusted to the digital age, such as the five barriers published by Ram and Sheth (Kuisma et al., 2007; Ram & Sheth, 1989). This basis thus requires an adjustment to the present IS environment to cover barriers more accurately. We target this shortcoming by refining previous concepts. The extension of prior theories of resistance will establish a more accurate and up-to-date basis to map resistance in upcoming information system (IS) technologies.

Thirdly, literature distinguishes three sources of resistance: namely consumer-based, product-based and channel-based resistance plus its interaction (Black, Lockett, Ennew, Winklhofer, & McKechnie, 2002). The vast majority of studies has been devoted to consumer and product characteristics, but little is known about the impact of channel characteristics (Maity & Dass, 2014). As theorized in task-technology fit literature, a clear understanding of channel characteristics is pivotal to mastering channel resistance, as these form the basis to establishing a task-technology fit (Larsen et al., 2009; Simon & Usunier, 2007). Our study is therefore primarily dedicated to channel characteristics in combination with product characteristics. For this purpose, a qualitative rather than a quantitative approach ought to substantiate prior findings (Coursaris & Kim, 2011; Mallat, 2007) by uncovering the key defining components of m-commerce resistance for complex products. This provides a solid basis for future investigations.

The article starts with a review of literature about the barriers of m-commerce in section 1. In this context, relevant barriers will be incorporated in a model to build a common basis for the interpretation of the value-chain linkages. In section 2 the evaluation method is introduced. Subsequently, the interview results were presented and discussed in terms of theoretical and practical implications next to limitations and future research in section 3.

3.3 Theoretical Background

Ram and Sheth (1989, p. 6) defined innovation resistance as “the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure”. Innovation resistance can be characterized by the time of adoption (i.e. for early adopters vs. laggards), the degree of adoption (i.e. active vs. passive resistance) and the degree of innovation including the extent of discontinuity and the extent of conflict with a consumer’s belief structure (Ram & Sheth, 1989). As a profound explanation for resistance, the status quo bias theory names numerous psychological effects that lead to misperceptions of the established state, and drive the protection of status quo. Commonly mentioned were the transition and uncertainty costs, loss aversions, anchoring effects, regret avoidance, loss of control, psychological dissonance or self-perception theory (see Samuelson & Zeckhauser, 1988). Ram and Sheth (1989) concluded that resistance is an instinctive response of humans, whose processes need to be analyzed. The means-end approach provides an appropriate method to accomplish this for several reasons. At its core it differentiates three hierarchical levels: product or service attributes (A), consequences of product usage and service consumption (C), and values as the desired end-states of consumers (V). The means-end perspective is analogous to the expectancy-value theory (Rosenberg, 1956), which delineates consumers' inclination to refer experienced consequences to attributes of past decision behavior in product encounters. Consequently, consumers learn to choose attributes that are instrumental to their desired consequences (Reynolds & Gutman, 1988), such as the selection of the most supportive channel to ensure a good product choice. Consequences are antecedents to desired "end"-values such as self-actualization (Xiao, Guo, D'Ambra, & Fu, 2014). In the course of resistance research, the means-end relation might cause confusion, since it captures the antagonists of certain goals, contrary to means in its original sense. Means are therefore referred to as antagonists in this article. In the next section, the literature on IS barriers is reviewed based on the presented A-C-V structure.

3.4 Research Objectives

3.4.1 Attributes.

Literature revealed several concepts that addressed attributes as antecedents to m-commerce resistance. Put simply, online purchase intention is determined by a computer and a human factor (Hausman & Siekpe, 2009) or, in other terms, a technical and a service component that impact the intention to purchase products online (Khare, Dixit, Chaudhary, Kochhar, & Mishra, 2012). Drawing on the information systems success model by Delone and McLean (2003) three factors built the origin of IS success or failure, that is the system, service and information quality. System quality captures the engineering-oriented aspects of m-commerce and for instance comprises appearance, technical adequacy, delay, navigation, security, and privacy, which has recently be extended by factors such as audio-visual support, user customization, and virtual reality (Ahn, Ryu, & Han, 2007). Transferring the IS success model to system quality in m-commerce, prior studies saw a small screen, limited bandwidth, connection stability, limited power supply and slow processing as reasons for the inferior system quality. Consumers also complained about a lack of security, and shortcomings in the system, which caused vulnerability in terms of data exposure and self-induced errors (Cao et al., 2014; Laukkanen et al., 2007). Zhou (2011), on the other hand, emphasized the criticality of system quality as the most important antecedent to ease of use. This emphasizes the importance of a clear layout, effective navigation, reliable connection and a convenient screen size, all of which are often difficult to obtain in m-commerce. A major reason for m-commerce reluctance may thus be the technical shortcomings and a poor interface.

Service quality refers to the means that facilitate an efficient and effective purchase in an IS (Zeithaml et al., 2002). Zeithaml et al. (2002) identified 11 features that are counterproductive to the perception of e-service quality; namely the lack of reliability, responsiveness, access, flexibility, ease of navigation, efficiency, assurance and trust, security and privacy, price knowledge, site aesthetics and customization, and personalization. In terms of complex businesses such as insurance, the absence of these service attributes hinders the technology acceptance (Devlin, 2007; Keh & Sun, 2008), since it forces consumers to make a significant search effort, to face lengthy and incomprehensible policies and to make choices under uncertainty. Mobile purchases for complex products can consequently become unviable (Laukkanen et al., 2007). Examples of poor service are the lack of an official receipt, a non-tailored, one-fits-all service, or an unclear proceeding at the mobile's display (Cao et al., 2014; Kuisma et al., 2007).

Lastly, information quality defines the performance of an IS in providing information such as insurance policies (Zheng, Zhao, & Stylianou, 2013). Common dimensions are information accuracy, comprehensiveness, reliability, completeness or timeliness (Ahn et al., 2007; Delone & McLean, 2003; Doll & Torkzadeh, 1988; Liang & Chen, 2009; Palmer, 2002; Rai, Lang, & Welker, 2002). It has become a fundamental prerequisite to enable a self-managed purchase in m-commerce (Zhou, 2011, 2013). Nonetheless, scholars stressed the lack of trust in the quality of information that is provided in IS (Laukkanen et al., 2007), for instance in terms of completeness or accuracy. Prior investigations found the lack of information to be a crucial reason for the reluctance to use new channels such as internet and mobile banking (Kuisma et al., 2007; Sripalawat, Thongmak, & Ngramyarn, 2011). Gurtner (2014) argued that new channels lack independent information sources such as expert panels, society and public media. Moreover, compensation driven businesses, such as those commonly found in the insurance field, are often seen with suspicion with regards to honesty (Straughan & Lynn, 2002). Consumers therefore mainly engage in a "research online, purchase offline" behavior (Jin, 2012) in order to gain assurance through different independent sources. Conclusively, the three areas of system, service and information quality seem to pose the majority of resistance attributes. To enhance the understanding, the following research question is targeted: *Which attributes and category of attributes are most detrimental to the adoption of m-commerce in the insurance business?*

3.4.2 Consequences.

The vast majority of approaches towards innovation resistance have dealt with factors on the level of consequences, such as emerging risks or mistrust (Yang, Lu, Gupta, Cao, & Zhang, 2012; Zhou, 2013). These approaches help to assign relevant attributes to a more abstract level and are thus introduced in more detail here. Probably the most established innovation resistance theory was published by Ram and Sheth (1989). It consisted of two main categories of barriers - a *psychological and a functional category*. The psychological barrier is further split into a *tradition and an image barrier*, whereas the tradition barrier circumscribes the degree of cultural change that an innovation evokes from consumers' perspective. For instance, m-commerce is commonly criticized for abolishing social interaction and making agents obsolete. This might be conflicting with social norms and societal values and thus cause incompatibility with one's own tradition (Gurtner, 2014). The image barrier therefore embraces the perceptual stereotypes that are inherent to an innovation; for example, insecurity of payments via hand-held devices, their propensity for data misuse and the lack of information. The functional barrier on the other side is divided into a *value, usage and risk barrier*. The value barrier embodies the net-benefit of channel usage, capturing the input-output ratio in comparison to channel substitutes. For insurance, contemporary product encounters in m-commerce add little value compared to product encounters in traditional channels due to less service and information provision, less security, less privacy and higher prices (Heinze & Thomann, 2015). The usage barrier defines the incompatibility of an innovation with existing practice or habits such as the common contacting of an agent when a product refinement is necessary. Lastly, the risk barrier is further split into a physical risk (defined as harm of oneself or ones property), economic risk (defined as financial loss), functional risk (defined as product malfunctioning) and social risk (defined as social ostracism and ridicule). By applying these barriers Laukkanen et al. (2007) investigated the mobile banking resistance. He found the greatest impact for the value barrier, indicating no significant merits of mobile banking. In addition, the usage barrier generally affected the adoption, while image and risk barrier were more of an issue among seniors. The tradition barrier had no significant effect. Apart from this, research on risk barriers has significantly advanced in the past decade. Yang et al. (2015) recently published eight prevailing risk dimension that are relevant to consumers in the product encounter. Next to the economic, function and social risk, they incorporated a security, time, privacy, service and psychological risk. Contemporary literature generally agrees on five risks that are also shared by the afore-mentioned concepts. These are: economic (also financial), function (also performance), time, privacy and psychological risk (Crespo et al., 2009). Similarly, scholars outlined three main switching barriers: financial costs - referred to as loss of monetary resources; procedural costs – such as the time and effort costs; and relational costs - such as the costs arising from psychological and emotional discomfort (Burnham et al., 2003). In Table 3.1 we reviewed and listed central barriers from the current literature.

Table 3.1 *Review of Barriers in Innovation Adoption.*

Author	Focus	Barriers in Innovation Adoption
Ram and Sheth (1989)	Technological Innovations	Usage Barrier, Value Barrier, Risk Barrier, Tradition, Image Barrier
McCreadie and Rice (1999)	Access to Information	Physical, Cognitive, Affective, Economic, Social and Political Influences / Constraints
Foscht, Essinger, and Kraigher-Krainer (2001)	Internet Shopping	Risk, personal contact, internet experience, complexity, purchase procedure / logistics, search, transparency, presentation
Vrechopoulos, Constantiou, Sideris, Doukidis, and Mylonopoulos (2003)	E-Commerce	Complicated use, lack of security, poor quality of service, high price for mobile access, inconvenience of devices and lack of personalization
Burnham et al. (2003)	Long-distance and credit card industry	Economic risk, evaluation, learning, and setup costs (= Procedural Costs), benefits loss and financial-loss costs (= Financial Costs), personal relationship loss and brand relationship loss costs (= Relational Costs)
Pagani (2004)	Mobile Multimedia Service	Lack of ease of use and navigation, limitation in bandwidth, cost, hardware and software functionality and privacy
Heres, Mante-Meijer, and Pires (2005)	Broadband Mobile Internet	Technical infrastructure, available substitutions, price, design of technology, usability, availability of service, visibility and testability (= technological barriers), Skills, capabilities and financial situation (= individual barriers)
Balabanis et al. (2006)	E-Stores	Familiarity, Convenience, Parity, Economic, Speed, Unawareness, Emotional Barrier
Bouwman, Carlsson, Molina-Castillo, and Walden (2007)	Mobile Services	Physical, Cognitive, Security and Economic Barrier
Kuisma et al. (2007)	Internet Banking	Resistance to Change, Control, Safety, Economy, Efficiency, Convenience
Cao et al. (2014)	M-Commerce and E-Commerce	Small screen size, inconvenient input, unstable and low-speed wireless connection (= technological deficits)
Yang et al. (2015)	Online Payment	Economic, Function, Security, Time, Privacy, Social, Service, Psychological Risk

To increase the transparency about relevant barriers in m-commerce, the following second research question is posed: *Which consequences are most problematic to the adoption of m-commerce and from which attributes do they stem?*

3.4.3 Values.

In the means-end theory, values can be both characterized as instrumental goals, and terminal values, which build upon these goals. However, literature on technology resistance often blends the value levels. This shortcoming is addressed in the present article by segregating goals from its higher order values. Based on a factor analysis, Balabanis, Reynolds, and Simintiras (2006) postulated seven barriers similar to instrumental goals. Adjusted to m-commerce, this is a *convenience barrier* as the inconvenience caused by emerging channel adoption costs (i.e. search costs), a *familiarity barrier* as the experience bias for one particular channel compared to others and the *unawareness barrier* as the unawareness of concurring channel alternatives and the resulting search costs (procedural costs). Further related to procedural costs, the authors stated a s*peed* and *parity barrier* that cover the IS processing or delivery time and the lack of alternative attractiveness for other channels, respectively. The e*conomic barrier* captures the price and credit options provided by alternative channels referring to financial costs. Lastly, it captures the *emotional barrier* as the emotional attachment to a certain channel combined with the risk of losing inherent benefits through switching (relational costs). Kuisma et al. (2007) investigated resistance to online banking by applying the five barriers postulated by Ram and Sheth (1989). They established six values that are affected by attributes and the related consequences: *economy, safety, control, efficiency* and *convenience value* augmented by a *general resistance to change value*. We next attempted to merge redundant and overlapping values based on their definition.

For *instrumental values (goals)* this led to five salient goals that are impeded by the lower-order categories: Firstly, prior models all include an *economic value*. This combines all financial aspects which inhibit the adoption of a new channel and arises from the cost-benefit ratio. For example, a provider offers a mobile travel insurance policy for a daily premium of 90 cents in m-commerce, but for €9.80 per year in e-commerce and offline. Secondly, all theories delineate a functional risk or the lack of an added value compared to purchasing in a conventional channel. The barrier can thus be defined as consumers’ fear of receiving an inferior product quality or experiencing quality stagnation when switching to m-commerce. This goal is termed as *performance value*. For example, people may fear overlooking relevant contract details on small displays, which undermines the key objective of insurance: to provide people with safety. As an example, a recent mobile insurance (m-insurance) policy insured ski equipment, but covered only theft from a locked ski cellar or a locked car, but not while on the slopes. A third relevant value can be summarized as *convenience value*. It synthesizes the prior named dimensions of relational and convenience loss (Balabanis et al., 2006) and arises from the potential regression of an established process status quo. Contrary to the performance value, the convenience value focusses on surrounding factors of the purchase process, rather than the product itself. Collier and Kimes (2012) define convenience as all kinds of time-based and cognitive efforts that emerge before, during or after a transaction. Reasons can be poor usability and interface issues as theorized by the usage barrier, but also the lack or loss of routines along with trust, control and familiarity, which had already been established in former channels (Falk et al., 2007; Langer, 1983; Samuelson & Zeckhauser, 1988). In consequence, procedural costs and time costs result. For instance, Kuisma et al. (2007) mentioned the lack of an official receipt, which confirms the contract details and provides control. A fourth goal that can be extracted from prior studies is the *secure privacy value*. This is defined as the desire for a segregation of business matters from a private life free of foreign intrusions. This corresponds to the security and privacy risk as mentioned by Yang et al. (2015). For example, gathered data such as user location, transaction details or addresses can be tapped by third-party providers, which might cause spam or data abuse. Lastly, scholars stressed the influence of social and traditional ties, which we summarized as *compatibility value*. It involves the need for conformity with social customs and traditional habits. Though we considered compatibility in our evaluation, it is noteworthy that past investigations attested a minor role of social and traditional risks (Crespo et al., 2009; Featherman & Pavlou, 2003; Lee, 2009) for businesses such as insurance. To improve existing insights, this study targets the following third research question: *Which instrumental values are most affected by the usage of m-commerce in the insurance industry?*

Terminal values are desired end-states that form consumers' "self" and reflect central needs, which underlie their motivation. Howard (1977) pointed out that terminal values are causal to product class decisions similar to channel choice. Pitts, Wong, and Whalen (1991) tested nine terminal values: self-respect, security, excitement, fun and enjoyment in life, gaining respect, self-fulfillment, a sense of belonging, a sense of accomplishment, and cordial relationships with others. Pai & Arnott (2013) posed seven terminal values in the context of social network usage: self-actualization, self-direction/control, belonging, conformity, selfesteem, hedonism, and reciprocity. In the context of an insurance policy purchase, particularly the aspect of security, self-actualization and self-direction/control seems to be reasonable, whereas hedonistic and social values ought to be less influential. This corresponds to values reported by Kuisma et al. (2007) for internet banking, embracing safety, control, efficiency and resistance to change (next to the goal-related economy and convenience as mentioned above). In this sense, efficiency can be understood as an antecedent of self-actualization, which we define as leeway to realize one's own endeavors. In conclusion, security, self-determination and self-actualization seem to be hampered in the course of an m-insurance purchase. To answer this assumption, the following question is posed: *Which terminal values stem from the instrumental goals and are most affected in the course of m-insurance commerce?*

3.5 Methodology

The evaluation of data is based on three main steps: First, laddering interviews are conducted to uncover linkages between channel attributes, consequences and values. Second, the content is coded according to defined categories to build means-end chains from the obtained linkages. Third, the resulting chains are depicted in an implication matrix and aggregated in a hierarchical value map (HVM) including the most significant ladders. In the following we will explain the basic means-end approach and the methodological steps in more detail. The subsequent sections partly follow the reporting of Pai and Arnott (2013) as an actual example of means-end research.

3.5.1 Sample.

In order to gain data from "resistant" consumers the sampling of this study consisted of policy holders who had not adopted m-commerce. The pre-selection ensured that all participants were in possession of both current insurance contracts, and mobile devices, and were also aware of m-insurance but had not yet used it. In total 20 consumers were interviewed, which suits the minimum requirement of sample size (Reynolds & Olson, 2001). Demographic and sociographic data (see Table 3.2) were evaluated initially by a defined questionnaire read out loud by the interviewer[6]. The average age was 31.25 years, which reflects the relevant target group of m-insurance. Gender was equally distributed at 50%

[6] The evaluation of interviews in this study was partly executed by Matthias Thomann in context of his master thesis, which was supervised by me. He further supported the coding of the interviews together with a third independent coder in order to control for interrater-reliability.

each. The majority of respondents worked as employees (nine persons), a further four were still studying, three worked in the public sector and another three were employed in an executive role. One respondent was engaged as an apprentice. In total, there were 167 insurance contracts between all the participants, with 75% that used an agent, broker or bank advisor and 25% that already used e-commerce as their sales channel. Fourteen of the participants (70%) used their smartphones or tablets on a daily basis while just six (30%) used it once a week or less. The interviews ranged in their duration from 17 to 58 minutes, with an average of 36 minutes, close to the suggested reference value of 45 minutes for laddering interviews (Gengler, Klenosky, & Mulvey, 1995; Reynolds & Gutman, 1988).

Table 3.2 *Socio-Demographic Overview of the Sample.*

Measure	Item	N	Percentage / Ø
Gender	Male	10	50%
	Female	10	50%
Age	18-25	8	40%
	26-35	8	40%
	36-45	2	10%
	46-55	1	5%
	≥ 56	1	5%
			31.25
Education	No schooling completed	0	0%
	Lower secondary school	1	5%
	Secondary school certificate	6	30%
	Advanced school-leaving certificate	4	20%
	Graduate	9	45%
Profession	Apprentice	1	7%
	Student	4	27%
	Employee	12	60%
	Executive	3	20%
Product Experience	Amount of contracted insurance	167	8.35
Channel Preference	Agent	10	50%
	Broker	1	5%
	Bank Advisors	4	20%
	Internet	5	25%
Device Ownership	Smartphone	20	100%
	Tablet	13	65%
Device Usage	Daily	14	70%
	Weekly	3	15%
	Less than weekly	3	15%

On average, each respondent revealed 4.35 ladders with a mean length of 4.58 steps, which both slightly exceeded observed values of two to three as outlined by Reynolds and Gutman

(1988) or Pieters, Baumgartner, and Allen (1995). However, this deviation is not surprising, since we considered the broad field of insurance in general, contrary to simple goods or behavior as often referred to. Moreover, as afore-mentioned, there is still high ambiguity towards m-insurance, which provides plenty of obstacles to consumers' non-adoption, leading to higher numbers of resistance ladders.

The interviews took place during August to September 2014 and were conducted by two interviewers, both of whom had expertise regarding interviewing in general and the specific laddering approach. The semi-structure of the interview was prepared by considering recent literature and tested in three pre-test interviews, with subsequent discussion of discrepancies and ambiguities. All three test persons were well experienced in the field of m-commerce in order to obtain critical and constructive feedback. A summary of the semi-structured interview guideline is shown in Table 3.3.Table 3.3 *Guide of the Interview*

Table 3.3 *Guide of the Interview.*

Procedure	Time	Semi-Structured Procedure and Questions
Opening	5	1.1 Introduction of Interviewer and Background 1.2. Explaining the Situation - M-commerce in the Insurance Market 1.3. Explaining the Purpose - Customer oriented conception of m-insurance 1.4. Introducing the Interview Procedure 1.5. Data Usage and Privacy
Warm-Up	5	2.1. Evaluating Socio- & Demographics 2.2. In which Situations do you use your Smartphones / Tablet? 2.3. For which purposes do you use your Smartphone / Tablet? 2.4. Have you ever bought something via Smartphone?
Generation of Attributes	10	Preference / Difference Method: 3.1. What is your preferred way of buying insurance? 3.2. In comparison to the preferred channel, which attributes of Apps would prevent you from buying insurance? 3.3. Please rate these attributes (from 1 to 6).
Laddering	20	4.1. Explaining the Laddering Method Repeating questions (probing), No right or wrong answers, Starting from the most to the least important attribute 4.2. Probing Procedure i.e. Why is that important to you? What is your typical response to that? What are the disadvantages for you? What would happen if...?
Closing	5	5.1. Concluding Questions and 5.2. Signing the Informed Consent

3.5.2 The Means-End Approach.

The means-end approach has become “one of the most promising developments in consumer research since the 1980s” (Grunert et al., 2001, p. 63) by uncovering perceptual processes of consumers engendered by a product or channel (Walker & Olson, 1991). The means-end theory is based on a cognitive view, modelling human experience and other types of information as different categories which are linked in networks (Grunert & Grunert, 1995). Means-end chains reflect an excerpt of these network linkages. The linkages emerge in the process of past purchases in which consumers evolve specific associations between product attributes and induced consequences. Based upon this, consumers can deduce the channel attributes that are instrumental in reaching their intended goals (Reynolds & Gutman, 1988) and scan new channels regarding the presence (i.e. sufficient information, privacy) and absence (i.e. no advisor) of the desired attributes prior to purchase. The negativity of the attributes and their consequences depend on the desirability associated with a goal that is pursued (Pieters et al., 1995). For example, requiring a significant handling effort obstructs the goal of experiencing a convenient purchase process, and thus makes it an avoidable consequence, although a high level of convenience for an insurance purchase is not always expected. The means-end approach assumes a hierarchical structure of the attributes, consequences and values. As illustrated in Figure 3.1 Walker and Olson (1991) differentiate between channel knowledge (also product-related) and self-knowledge. The former consists of concrete and abstract product and channel attributes, leading to functional consequences. Self-knowledge further consists of psychosocial consequences as well as instrumental and terminal values. We classified the interview statements according to these dimensions, starting on the level of abstract attributes to reduce the variety of attributes, which is consistent with the prior literature.

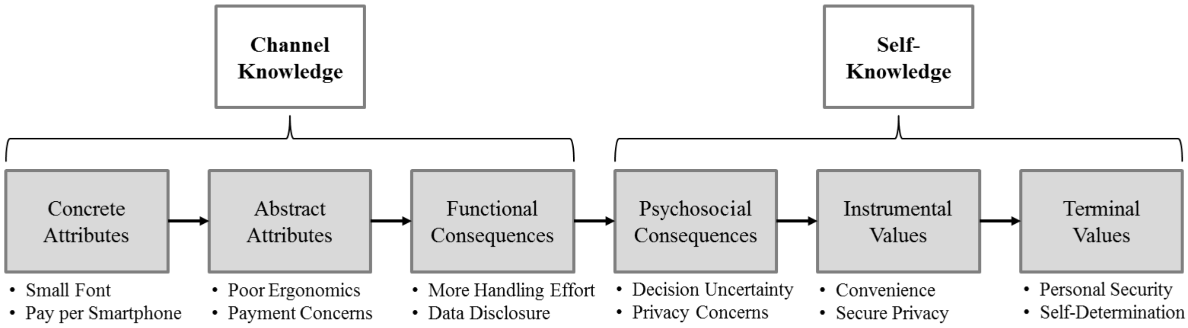

Figure 3.1 Channel and self-knowledge in a means-end chain. The figure is adapted from Walker and Olson (1991).

IS research has applied the means-end approach to investigate online shopping (Lin & Wang, 2008), perceptions of service quality (Zeithaml, 1988), the adoption of online applications (Chiu, 2005) and social networking usage (Pai & Arnott, 2013). Kuisma et al. (2007) emphasized the usefulness of the means-end approach to shed light on resistance factors to adopt complex products such as online payment. Taking compatibility to the mobile environment and complex insurance services, the means-end approach builds a suitable basis to analyze barriers for m-insurance. To uncover means-end chains Reynolds and Gutman (1988) propose the usage of in-depth interviews labelled as "laddering" interview.

3.5.3 Laddering Interview.

The laddering interview describes a semi-structured one-on-one interviewing technique, which helps consumers to reflect about personal attitude-consequence-value relations. This leads to a precise understanding of underlying motives for channel resistance. During the interview process, interviewees were encouraged to reproduce "nonconscious" means-end chains, termed as ladders. This was accomplished in two steps; starting with the elicitation of the most relevant attributes (i.e. by asking for preference-consumption differences), followed by laddering probes typified as "Why is that important to you" questions. These questions supported the consumer in building up their own A-C-V sequences (Reynolds & Gutman, 1988). As recommended in the literature, we used different techniques to support consumers in laddering. Initially, a realistic situational context was established by asking for each interviewee's preferred way of purchasing insurance to establish a context for further questions about m-commerce. Moreover, interviewees were asked to reflect on the *absence of certain objects or states*, and reasons why they do not do certain things, termed as *negative laddering* (Reynolds & Gutman, 1988). An exemplary A-C-V ladder could include the "lack of a paper proof" (A) leading to "insufficient product clarity" (C1) leading to a "lack of trust in this product" (C2) impeding the "products performance to provide safety" (V).

The laddering method supports two ways in proceeding, a *"soft"* and a *"hard" laddering* approach. The former follows the interviewee's natural flow of speech, and allows forks, loops and blind alleys (Grunert & Grunert, 1995; Zanoli & Naspetti, 2002), whereas hard laddering forces the consumer to build up ladders one-by-one and does not require an interviewer. However, soft laddering is supposed to be beneficial in contexts of low experience with the object of investigation, as can be assumed for m-insurance. Thus the flexible steering through an interviewer was chosen in this investigation.

3.5.4 Coding Procedure.

We used MAXQDA® Software to rebuild means-end chains from the interviews. Coding was undertaken by first inspecting the content for salient ladders according to the A-C-V levels. Concepts with similar meaning were summarized under a common code. The coding was conducted in four steps. First, one of the two interview leaders started to build up a list of codings based on the interview data. Second, these categories were discussed in a session among the interview leaders. This was necessary to synthesize the contextual knowledge of both in order to prevent misinterpretation. In a third step, we followed the recommendation of Grunert et al. (2001) in applying a parallel coding, including one of the interviewers and a second blind coder. In line with Subramony (2002's) procedure, the blind coder was provided with around 40% of ladders hidden in the interviews, which builds a satisfying indication for the interrater reliability. Resulting discrepancies regarding the coding were again discussed and adjusted. The final interrater reliability (Cohen's κ) was .67, which included additional or missing values (when more linkages were found). For categories that were identified from both coders (excluding missing values) a Cohen's κ of .80 resulted. With regard to established recommendations, both values reveal substantial interrater reliability and provide a solid basis for further investigations (Landis & Koch, 1977).

After the content to category assignment, all retrieved ladders were listed in a table, which served to form a matrix of A-C-V associations, termed the implication matrix. To avoid overestimation of linkages (Gengler et al., 1995; Reynolds & Gutman, 1988), we dropped equal parts in ladders mentioned by one single person. For instance, if one person built up a ladder from 10-14-21 to 23 and a second ladder with 10-14-18 to 25, we did not count the 10-14 linkage a second time for this person. Finally, the coding resulted in 10 categories for attributes, 11 categories for consequences and 9 value categories, revealing a total of 30 categories. A summary together with category definitions and the amount of citations and respondents who mentioned the category is given in Table 3.4. Sample citations for each category are additionally shown in Appendix 8.2.

Table 3.4 *Overview and Definition of Attributes, Consequences and Values.*

No.	Category	Citations[a]		Respondents[b]		Definition
1	Limited Choice and Monopolism	7	6%	5	25%	Limited, pre-selected and biased information due to single source, no comparison
2	Poor Ergonomics	23	19%	14	70%	Poor usability, interface and content presentation leading to tedious handling
3	Inferior Information Content	9	7%	7	35%	Unclear, imprecise, incomplete information content

Table 3.4 *Overview and Definition of Attributes, Consequences and Values. (Continued)*

No.	Category	Citations[a]		Respondents[b]		Definition
4	No Personal / Individual Contact	10	8%	9	45%	No human, personal interaction or consideration of individual needs
5	Payment Concerns	13	11%	10	50%	Lack of payment options, effort to fill in credentials, no transparency about debits and data storage
6	Uncertain Data Handling	20	16%	14	70%	Uncertainty about the usage of data
7	Image Discrepancy	9	7%	5	25%	Misfit between the technology characteristics and those of insurance
8	Technical Insufficiency	7	6%	6	30%	Technical inferiority through limited bandwidth, connection stability, limited power or performance
9	No Service Advice & Support	16	13%	14	70%	Lack of service options to facilitate the process and to cover specific consumer needs
10	No Paper Proof	8	7%	7	35%	No printed proof of contract details
11	Lack of Documentation and Clarity	11	5%	7	35%	Insufficient basis to check, review, verify or revise contract conditions
12	Process Effort Takeover	15	6%	7	35%	Takeover of essential process steps from other instances such as agents
13	Limited Scope of Action	7	3%	5	25%	Loss of leeway to act through restriction of information and choice options
14	Handling Effort and Mistakes	23	10%	15	75%	Effort to adopt and manage the technology and effort through handling errors
15	Insufficient Decision Basis	28	12%	16	80%	Lack of sufficient and trustworthy information to obtain enough certainty to purchase
16	Data Disclosure	24	10%	13	65%	Intentional and unintentional disclosure of data to third-parties & data theft
17	Lack of Trust and Mistrust	21	9%	12	60%	Lack of credibility in the provider market
18	Privacy Concerns	18	8%	11	55%	Loss and publication of private information to third-party entities
19	Financial Burden	24	10%	13	65%	Financial disadvantages arising through unexpected costs
20	Choice Uncertainty	40	17%	19	95%	Ambiguity about product details
21	More Time Effort	29	12%	17	85%	Increase of the required time investment
22	Convenience	40	23%	17	85%	Desire to minimize time and cognitive effort surrounding the transaction process
23	Economy	27	16%	15	75%	Desire to obtain a good cost-benefit ratio
24	Performance	35	20%	20	100%	Desire to have safety assured through proper product functioning of the insurance
25	Privacy	11	6%	11	55%	Desire for private life to not be intruded upon
26	Compatibility	2	1%	4	20%	Desire to create harmony with own social and traditional values
27	Material Security	12	7%	10	50%	Value to secure one’s own property
28	Personal Security	2	1%	2	10%	Value to secure one's own life
29	Self-Determination	7	4%	6	30%	Value to control one`s own data and matters
30	Self-Actualization	36	21%	18	90%	Value to have leeway to realize one’s own endeavors

Notes. [a] The numbers reflect the absolute value and the percentage of notions for the according level, e.g. attributes. [b] The numbers reflect the amount of persons (n_{max} = 20), who noted this category and the according percentage.

3.5.5 Implication Matrix.

An implication matrix provides the basis to sort out dominant ladders for the HVM, by aggregating all direct and indirect linkages and is shown in Table 3.5. Unlike direct linkages, indirect linkages occur when two categories are connected via an intermediary within one ladder, for example A-B-C has a direct connection between A-B and B-C and an indirect connection between A and C. The implication matrix can be read by first skimming along the attribute rows until a salient value above a predefined cut-off is found, second by taking the code number of the connected category to again read along its row and third by repeating the process until the end of chain is reached.

3.5.6 Hierarchical Value Map.

The HVM reflects the means-end chains by graphically illustrating salient A-C-V linkages in a tree diagram (Reynolds & Gutman, 1984). It facilitates the understanding by (1) illustrating the observed set of concepts, (2) showing the related level of abstraction (A-C-V) and (3) drawing the linkages between these concepts (Gengler et al., 1995). Consistent to prior evaluations (Pai & Arnott, 2013; Pieters et al., 1995) we referred to the direct linkages as the basis of the HVM. To increase meaning, scholars simplified the HVM by cutting linkages below a relevant level, as for instance a cut-off of four for samples with 50 respondents (Reynolds & Gutman, 1988). Others also argued a cut-off of two for samples around 20 to 30 (Pai & Arnott, 2013; Subramony, 2002). This choice is a trade-off between retaining detail and enabling interpretability (Pai & Arnott, 2013). In this article, the HVM should primarily be used to give an overview on the most significant relations, in complementation to the comprehensive implication matrix. We thus decided to base our HVM on a flexible solution by taking a cut-off of four regarding the direct connection of attributes and consequences and subsequently filtered direct associations that were equally to or above four, unless no such values were available. In this case, we broke down the cut-off according to the next strongest association. Given an example from the implication matrix (Table 3.5), Payment Concerns and Lack of Documentation are connected by four notions, while the strongest association between Lack of Documentation and Lack of Trust is just three, which is still selected for the reason of the highest available linkage. In total, the picked linkages in the HVM covered 49% of all direct linkages.

3.6 Results and Discussion

The analyzation of results draws on the implication matrix as well as the derived salient means-end chains as depicted in Figure 3.2. For a better understanding, representative citations are presented along with the main A-C-Vs in the following. In total, 10 significant chains were retrieved[7]. Referring to the implication matrix, four attributes in particular constitute the significant antagonistic properties counteracting against the intended goals. These are (1) poor economics, (2) payment concerns, (3) no advice and service support and (4) uncertain data handling, which were each named by at least 50% of all interviewees. The goals also had clear linkages to terminal values which also determine the conflicting focal points. Drawing on the number of notions, performance appeared to be the most conflicting value named by 100% of respondents, followed by convenience (named by 85% of respondents) and economy (named by 75% of respondents) next to secure privacy (named by 55% of respondents). Convenience turned out to be particularly associated with the value of self-actualization (14 direct linkages). Hence, performance was antecedent to material security (7 direct linkages), while economy was related to both material security (4 direct linkages) and self-actualization (3 direct linkages). The desire for privacy was mainly associated with self-determination (2 direct linkages).

3.6.1 Chains of High Salience.

As previously mentioned, we found four salient origins of m-commerce resistance, including poor ergonomics, payment concerns, no service advice or support and the uncertain data handling. With respect to the initially introduced classification into system, service and information related factors of resistance, no service and uncertain data handling can be assigned to service quality, while the poor interface relates to system quality. Payment concerns can be assigned to both, in dependence of the respective aspects that are mentioned (e.g. data security vs. handling effort to fill in credentials). In turn, interviewees were less

[7] In a first data inspection, we found discomfort and frustration to be a salient consequence in m-commerce usage. In total 90% of respondents reported that it was likely for them to end up with feelings of discomfort and frustration. Accordingly, each of the psychosocial consequences finally led to discomfort and frustration, while on the other side each goal was substantially connected to this category. We therefore dropped the category from the implication matrix, as it stipulated an on top third-level consequence and therefore concealed insightful relations between psychosocial consequences and goals. However, this has to be noted as it confirms prior literature, stating its mediating role between means and ends (Cunningham, 1967; Keh & Pang, 2010; Stone & Grønhaug, 1993).

concerned with aspects of information quality. In the following, the predominant chains of resistance are analyzed in more detail.

Poor Ergonomics: The respondents noted numerous concrete attributes that give the impression of a poor ergonomic in m-commerce. Among these, the great majority mentioned small display and font, along with the need to scroll and zoom as a consequence of the immense amount of information that have to be considered, as described in the following[8]:

> "Well, Apps come along with such a small display and (…) you never know, if you have scrolled down to the very end or if a link or something else is left." (Respondent 02, Poor Ergonomics)

Moreover, the respondents mentioned inaccurate touch response, the effort of having to type on a phone, poor navigation, too many clicks, unclear instructions and a lack of written summaries. Consequently, poor ergonomics have a considerable effect on the handling effort and the risk of mistakes that may arise through difficulty in using the interface. Consumers also mentioned the worry of overlooking or skipping important details, of accidentally paying twice for services, the high time and cognitive effort needed to complete forms, as well as long loading times.

> "This is particularly dangerous with mobile transactions. You can easily press the wrong button by accident and end up paying for a long-term contract which was not your intention..." (Respondent 17, More Handling Effort and Mistakes)

The noted issues were mentioned to lead to an increase of time effort, and uncertainty about the right choice. The latter was also associated with looming financial burdens, as a possible consequence of choosing unwisely.

[8] The shown citations are idiomatic translations of the original German statements into English, to better convey the specific message into the target language.

Table 3.5 *Implications Matrix.*

		Consequences											Value 1					Value 2				
		11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	∑
Attributes	01 Limited Choice and Monopolism		1.00	2.00		1.00		0.01		1.03	0.02	0.01	0.01	0.04				0.02			0.02	5.16
	02 Poor Ergonomics	1.00	2.00	1.00	8.00	3.00				0.02	0.06	2.06	0.10	0.03	0.04			0.02			0.06	17.39
	03 Inferior Information Content		1.00	1.00		3.02		1.01		0.03	1.04	0.01	0.02	0.02	0.03			0.02			0.02	7.22
	04 No Personal / Individual Contact		1.00	1.00		3.00		3.02	0.01	0.01	0.05	1.00	0.02		0.05		0.01	0.02			0.01	9.2
	05 Payment Concerns	4.00		1.00	2.00		5.00	1.02	0.01	0.03		0.04	0.03	0.02	0.01	0.04	0.01			0.01	0.01	13.23
	06 Uncertain Data Handling	1.00			2.00		11.00	1.01	1.09	0.02	0.01	0.02	0.04	0.05	0.01	0.05		0.01		0.03	0.03	16.37
	07 Image Discrepancy	1.00			1.00	2.00	1.00	3.01	0.02	1.01	0.05		0.03	0.02	0.01	0.01			0.01		0.01	9.18
	08 Technical Insufficiency				3.00			1.00	0.01	2.00		1.02	0.03	0.02	0.01						0.01	7.1
	09 No Service Advice & Support		6.00	1.00	2.00	5.02					1.06	0.06	0.07	0.01	0.06						0.03	15.31
	10 No Paper Proof	3.01	1.00		2.00	0.01		1.01			1.03		0.01		0.04					0.01	0.01	8.13
Consequences	11 Lack of Documentation and Clarity					1.00		3.00		0.01	2.02	1.00	0.01	1.01	1.03	0.01	1.00			0.02		10.11
	12 Process Effort Takeover					1.00		1.00		1.00	1.02	7.01	3.07	0.01	0.02			0.01			0.07	14.21
	13 Limited Scope of Action					1.00		1.01		2.01	0.02		1.00	0.02	1.01		1.00	0.01				7.08
	14 More Handling Effort and Mistakes	1.00				1.00	1.00		2.00	1.00	4.00	8.02	3.08	0.02	1.04			0.02		0.01	0.04	22.23
	15 Insufficient Decision Basis							2.00		3.02	15.01	2.01	0.05	0.05	0.10			0.04		0.01	0.04	22.33
	16 Data Disclosure							1.01	11.00	3.01	0.01	3.00	0.05	2.03	0.01	2.06		0.01		0.03	0.05	22.27
	17 Lack of Trust and Mistrust					1.00	2.00		2.02	2.02	9.01		0.03	1.04	3.05	1.03		0.02	0.01		0.03	21.26
	18 Privacy Concerns							1.00		1.00			4.00	2.00	0.01	6.01				2.03	0.04	16.09
	19 Financial Burden										1.00			16.01	3.00	1.00		0.05			0.02	21.08
	20 Choice Uncertainty									5.00		3.00	4.02	3.04	18.02	1.00		0.07	0.01	0.01	0.04	34.21
	21 More Time Effort										1.00		22.01		1.00					0.01	3.10	27.12
Values 1	22 Convenience																			1.00	14.00	15
	23 Economy																	4.00		1.00	3.00	8
	24 Performance																	7.00	2.00	1.00	2.00	12
	25 Secure Privacy																			2.00	1.00	3
	26 Compatibility																					
		11.01	12.00	7.00	20.00	22.05	20.00	20.11	16.16	22.22	36.41	28.26	37.68	25.44	28.55	11.21	2.02	11.32	2.03	7.17	23.64	

Notes. 1–10 = Attributes; 11–21 = Consequences; 22–30 = Values with 27 = Material Security, 28 = Personal Security, 29 = Self-Determination and 30 = Self-Actualization; dark grey highlights direct linkages from light grey to dark grey in the value order of ≥ 2, ≥ 3, ≥ 4; ≥ 5.

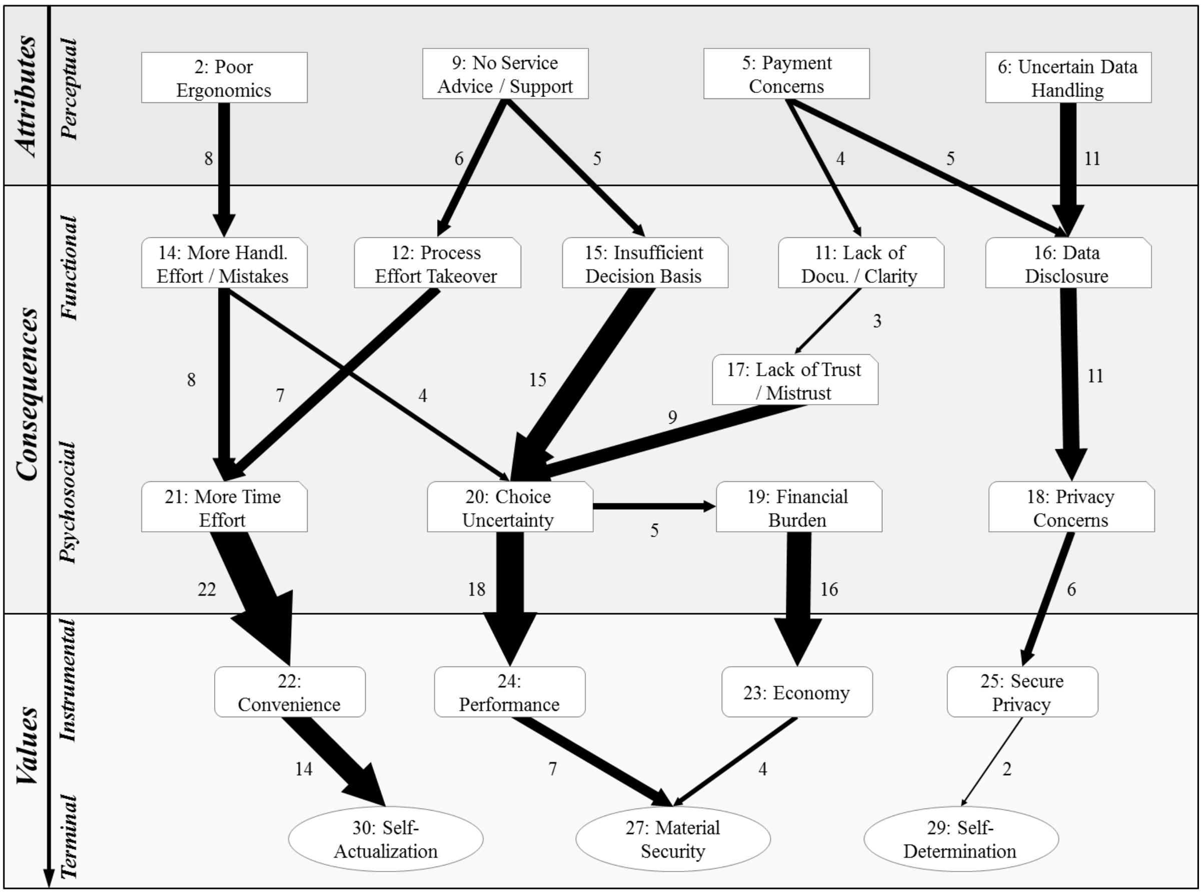

Figure 3.2 Hierarchical Value Map. Arrow thickness represents the amount of direct linkages according to the shown numbers.

Referring to the interviewees, the three consequences - time effort, choice uncertainty and financial burdens – are finally conflicting with the pursuit of convenience (discrepant to time effort and choice uncertainty), performance (discrepant to choice uncertainty) and economy (discrepant to financial burden). The respondents mainly reported that loss of convenience (e.g. through time loss) limits their leeway to engage in own interests (i.e. sports activities), confirming the negative effect of poor ergonomics on self-actualization. In the following citations this was described as follows:

> "I believe that time is the greatest commodity that people have in the current stressful age. And by spending less time in dealing with insurance purchases, I would gain more time for other things." (Respondent 18, Self-Actualization)

In addition, poor performance and economy were both mentioned as possible threats to one’s own material security, which thus constitutes the second conflicting linkage.

Payment Concerns: During the interviews several concerns regarding the payment process appeared. The most prevailing were related to data abuse. In this context, the consumers primarily noted the lack of knowledge about the debit process, the storage of payment credentials, unencrypted data transfer, a subsequent change of payment conditions and the lack of sufficient and trustful payment options (i.e. direct debit or Paypal). One respondent stated:

> "Because when switching to the app or the mobile channel it tells me to enter all my data all over again and I still feel uncertainty about mobile payment or online payment." (Respondent 15, Payment Concerns)

The concern over disclosure of data was associated with concerns over invasion of privacy and carried the risk of depriving consumers' of control over their own data. This is in conflict with the value of self-determination. An interviewee described this as follows:

> "...if it concerns sensitive data, I fear that someone might misuse it, which might harm me or bring unnecessary inconvenience. This could be direct advertising that I receive, such as spam, or identity theft in which my details are used to commit a crime or funds are stolen from my account." (Respondent 05, Data Disclosure)

In addition to the perils of data loss, consumers criticized the lack of proper documentation of payment details; for instance, seeing the debits on one's own account. It was mentioned that missing transparency about the cash flow is exacerbated when trust in the new technology is missing. This causes doubts about the chosen product manifested in choice uncertainty. A respondent concluded:

> "When the insurer charges the payments… I need transparency about the action that takes place in this moment" (Respondent 10, Lack of Documentation and Clarity)

Analogous to poor ergonomics this again jeopardizes the need for convenience, performance and economy and thus threatens the material security. For example, one respondent summarized:

> "I don´t want to pay a lot for low performance, that´s against the nature of humans." (Respondent 19, Economy)

Uncertain Data Handling: The uncertainty over data handling shows a clear linkage with data disclosure and privacy concerns referring to consequences. As the source of these concerns the interviewees mainly stated the fear of security gaps, since they estimated the technology to lack maturity; in terms of encryption, for example. Consequently, third-party access to private data was suspected:

> "One trusts apps even less than internet sites interestingly. Whereas the difference is not extremely big, one feels that internet sites (…) are better under own control…" (Respondent 17, Uncertain Data

Additionally, the access rights of some apps scared some of the interviewees. A common response was that interviewees wished to avoid personal profiling and tracking since this would empower insurance companies to infringe upon their life and to manipulate their behavior. For instance it was argued:

> "I don´t want to have my personal data go round in the internet. (…) That can have financial consequences too, such as when an app notices that I am always mountain-climbing and injure my ankle every six months. Then the insurance premium will rise accordingly." (Respondent 13, Privacy)

This ultimately produces a negative effect on the secure privacy, accompanied by a loss of control of consumers' own data, which raises several concerns: The respondents acknowledge that data may not only be visible to the insurer, but may also be leaked to an employer, friends or other parties. This impedes the pursuit of self-determination:

> "For instance, my medical record may get online for some reason (…) which would bring a feeling of absolute powerlessness." (Respondent 01, Self-Determination)

No Service Advice and Support: For the interviewed consumers a lack of service advice made them afraid of incurring the entire effort of the product choice. Thereby, the lack of service was mainly brought into relation to concerns about individual and specific queries that may arise while researching the product or later when the product is already in use. Moreover, consumers see better chances of purchasing a tailored product and to benefit from a trustworthy relationship when service is available. Another issue that was mentioned was the less ethical outsourcing strategy of service to the consumer similar to the Ikea principle and was mainly rejected. A respondent described the issue as follows:

> "The problem is that one normally has relative little knowledge about the insurance area. This means an insurance agent can at least give professional answers to some questions." (Respondent 03, No Service Advice and Support)

People accordingly stated that the takeover of the process reduces the confidence of making a good choice and greatly increases their time investment, which thus restricts the pursuit of convenience. This ultimately conflicts with the value of self-actualization.

In addition, a second means-end chain resulted, describing a significant insufficiency of the decision basis provided by the app. This originates from the technical restrictions in terms of inflexible and artificial responses to consumer queries, the withholding of information from the provider’s side, and the accidental overlooking of details. One respondent commented on the source of his concerns:

> "I would also fear that a provider offers me less information, compared to other distribution channels (…) and therefore my information situation, (…) would be worse right from the beginning." (Respondent 14, Insufficient Decision Basis)

Similarly, one interviewee stated a lack of interest in the product details. The insufficient decision basis drives feelings of uncertainty about the product choice, associated with fear of having no insurance coverage in severe situations (i.e. domestic coal) as summarized in the following:

> "And if then a case of damage comes up, I would not know at all, if this is covered..." (Respondent 01, Choice Uncertainty)

Thus, on the one hand this collides with the desire for proper service performance and conflicts with the value of material security. On the other hand, choice uncertainty reinforces the fear of financial costs. This finally thwarts the economy goal of the respondents and hinders the desire for material security.

3.6.2 Implications for the Research Questions

To answer the three initially stated research questions, we finally prioritized the extracted chains by calculating the sum of direct linkages between each construct along the chain as shown in Table 3.6. This revealed 15 high salient chains, which answers the research questions as follows: Firstly, the four most relevant attributes were poor ergonomics, no service and advice, payment concerns and uncertain data handling. Secondly, on the level of consequences, all of the five common risks, that is privacy, performance, time, financial and psychological risk appeared to be meaningful in the decision process with only marginal differences. The interviewees were most concerned about choice uncertainty, which is closely related to performance risk. Consistent with the findings of Laukkanen et al. (2007), time was among the highest risks, followed by financial risk and privacy. The factors of discomfort and frustration, termed as psychological risk, indicated a higher order by bundling the other risk dimensions. Thirdly, for the instrumental goals and terminal values, convenience and self-actualization were most likely in conflict with m-insurance which corresponds with prior findings (Collier & Kimes, 2012; Collier & Sherrell, 2010). The interviewees further stressed that m-insurance opposes the target of material security by restricting the economy and performance of the product. The desire for a secure privacy and its relation to self-determination ultimately played a minor, but still relevant role.

3.6.3 Chains of Moderate Salience.

There are five factors that fell just below the critical cut-offs, but seem noteworthy for the reason of their connection with highly salient categories. (1) This is the inferior information content, which was mainly antecedent to an insufficient decision basis. (2) Moreover, the human component and individual recognition of needs also appeared to be relevant to the consumers. They especially acted as driver for the lack of trust and mistrust besides an insufficient decision basis. (3) Some people further outlined the misfit of the image that an app has compared to the image of insurance (i.e. the playful technology versus the serious product) as antecedent to lack of trust and mistrust. (4) Additionally, technical insufficiency was highlighted by some respondents, and cited as a cause of increasing the handling effort and the risk for mistakes. (5) Finally, respondents noted the lack of a paper receipt, which primarily fuels the lack of documentation and clarity.

Table 3.6 *Overview of Most Salient A-C-V Chains.*

Sum of Direct Links	Chains and Corresponding Codes
52.03	Poor Ergonomics - More Handling Effort and Mistakes - More Time Effort - Convenience-Self-Actualization 2 14 21 22 30
49.02	No Service Advice & Support - Process Effort Takeover - More Time Effort - Convenience - Self-Actualization 9 12 21 22 30
45.04	No Service Advice & Support - Insufficient Decision Basis - Choice Uncertainty - Financial Burden - Economy - Material Security 9 15 20 19 23 27
42.05	No Service Advice & Support - Insufficient Decision Basis - Choice Uncertainty - Performance - Material Security 9 15 20 24 27
41.03	Payment Concerns - Lack of Documentation and Clarity - Lack of Trust - Choice Uncertainty - Performance - Material Security 5 11 17 20 24 27
41.02	Payment Concerns - Lack of Documentation and Clarity - Lack of Trust - Choice Uncertainty - Financial Burden - Economy - Material Security 5 11 17 20 19 23 27
40.00	Uncertain Data Handling - Data Disclosure - Privacy Concerns - Convenience - Self-Actualization 6 16 18 22 30
38.05	No Service Advice & Support - Insufficient Decision Basis - Choice Uncertainty - Convenience - Self-Actualization 9 15 20 22 30
37.02	Poor Ergonomics - More Handling Effort and Mistakes - Choice Uncertainty - Performance - Material Security 2 14 20 24 27
37.01	Poor Ergonomics - More Handling Effort and Mistakes - Choice Uncertainty - Financial Burden - Economy - Material Security 2 14 20 19 23 27
34.03	Payment Concerns - Lack of Documentation and Clarity - Lack of Trust - Choice Uncertainty - Convenience - Self-Actualization 5 11 17 20 22 30
34.00	Payment Concerns - Data Disclosure - Privacy Concerns - Convenience - Self-Actualization 5 16 18 22 30
30.02	Poor Ergonomics - More Handling Effort and Mistakes - Choice Uncertainty - Convenience - Self-Actualization 2 14 20 22 30
30.01	Uncertain Data Handling - Data Disclosure - Privacy Concerns - Secure Privacy - Self-Determination 6 16 18 25 29
24.01	Payment Concerns - Data Disclosure - Privacy Concerns - Secure Privacy - Self-Determination 5 16 18 25 29

3.6.4 Theoretical Implications.

This article fortifies m-commerce research in three ways: Firstly, by applying a qualitative approach, we drew a comprehensive picture of the psychological mechanisms that are central to m-commerce resistance. This closes the means-end gap of recent studies that strongly focused on the more abstract intermediaries (consequences) and values under usage of purely quantitative approaches (Coursaris & Kim, 2011). The presented results therefore provide a solid basis to approach m-commerce more thoroughly by understanding the fundamental attributes as well as their linkages to higher level factors that form consumers' attitudes. The applied five-level hierarchy as proposed by Walker and Olson (1991) improves the meaningfulness of simplified A-C-V structures, as for instance given by Ter Hofstede, Audenaert, Steenkamp, and Wedel (1998).

Secondly, our results contribute to the literature about the barriers in innovation adoption. The findings mainly correspond to prior models due to an obvious overlap of several postulated constructs (see Table 3.1). On the contrary, the establishment of a hierarchical structure refines past approaches. The posed structure clarifies prior incongruences, as for example the mixture of different levels as found in the models of Pagani (2004) or Yang et al. (2015), but also the extension of incomplete value sets as seen from Bouwman et al. (2007). Thus, the article gives an update and summary of previous concepts of innovation barriers.

Thirdly, the prioritized chains extend the knowledge on task-technology fit, by reinforcing the essence of service and system quality related aspects before information quality. In other words, for complex products m-commerce requires a task-technology plus service fit with special relevance of service and technology (system). This extends the set of variables that need to be synthesized in order to satisfy consumers in m-commerce. Our results accordingly shift the focus towards the sales environment (service and system) as a potential area for improvement, rather than the core product itself. As demanded, the identified channel characteristics strengthen an in-depth understanding of consumers' decision-making processes and buying behavior (Grunert & Grunert, 1995; Maity & Dass, 2014; Pai & Arnott, 2013).

3.6.5 Practical Implications.

As often mentioned in the literature, the means-end approach is of high value to understand the cognitions of consumers and to develop sophisticated positioning strategies (Reynolds & Gutman, 1988; Pieters et al., 1995). Firstly, there are concrete design implications. The found chains suggest a need to improve the ergonomics of smartphones and apps. This includes the enlargement of the displays, a clear user interface with structure and an improved handling to reduce click errors. The processor as well as the backend connection should be optimized to avoid long waiting times and jerking sites. Network operators can invest in bandwidth and Wi-Fi projects to provide a fluent user experience, steady mobility and no signal dead spots (Cao et al., 2014). Moreover, battery power needs to be extended; for instance by providing more stations for mobile device charging. Connection breakdowns need be covered with data backups.

Secondly, apart from the technical components, the content should be aligned with the channel attributes. This implies a reduction of content by providing summaries, visual explanations and tutorials, symbolic icons or audio advice to support consumers' learning and research process. M-insurance providers need to better integrate conventional service into the mobile environments and to adapt new service approaches. Froehle (2006) lists different types of face-to-screen service which seem helpful in this context. Among these, he differentiates between a technical mediated service such as a telephone hotline, chat or email, and technical generated service such as information buttons, FAQs, test and assurance seals, text summaries, online reviews, external links, email confirmation and references to selections of other buyers. Services need to be prepared accurately and staff should be trained to respond flexibly and be more consumer-oriented. In addition to improving service and ergonomics, consumers should be provided with alternatives methods of payment; for example, by credit card or direct debits. The security of data should be guaranteed and reimbursement assured in case of data theft or other fraud. Companies thus need to invest in a high technical security standard with safe logins and encryption criteria, but also a trustworthy treatment of all received information beyond technical security mechanisms.

Thirdly, the A-C-V chains provide different implications for the marketing of m-insurance: To reduce consumers' concerns, insurance companies need to disseminate the advantages of m-insurance, such as instant coverage when other services are not available, control and flexibility (Collier & Sherrell, 2010; Laukkanen et al., 2007). A common means is the enhancement of visibility by implementing "invite and share with friends" buttons as well as issue-related gadgets and gamification elements. An insurance app for ski equipment could, for example, implement a tracking function for completed skiing distances in competition with friends. Viral marketing could also help increase the knowledge about m-insurance; for example, by offering dynamic discounts the more often the app is shared.

3.6.6 Limitations and Future Research.

The present study holds some limitations and gives rise to future research. Firstly, the sample size fulfilled the minimum criteria for the means-end approach. An increase of the sample could easily change the outlook of the hierarchical value map and the related salient chains (Grunert & Grunert, 1995). Our result is thus a conservative approach to the relevant reasons of m-commerce resistance by applying a high cut-off and a small sample. Future research should build on these results with a more representative sample.

Although we applied different scientific criteria, in order to assure a valid categorization of the A-C-V ladders, the method still comes with leeway for interpretation. To substantiate this categorical system we suggest a validation of the found dimensions through a quantitative approach. This also addresses the examination of specific hierarchies among the applied risk dimensions. As outlined above, psychological risk displays a higher order position among other risks, while performance risk stimulates further risk dimension in m-commerce decisions.

Our study further investigated the barriers, but neglected the evaluation of countermeasures. This could be the subject of a subsequent examination which would match the barriers with possible solutions suggested by consumers or retrieved from a systematic market analysis. The obtained results highlighted service as a relevant variable in the task-technology fit literature. This implies the refinement of service according to the m-insurance specifics. To encourage a confident mobile purchase the combination of human and technological generated service seems promising. However, the migration and calibration requires more elaboration and should be subject to future research.

3.7 Conclusion

In this article we investigated the resistance of consumers towards m-commerce for complex products by exploring the underlying cognitive processes. A qualitative means-end approach was applied to unveil the linkages between channel attributes, their resulting consequences and conflicting values in the market of m-insurance. The results predominantly highlight the insufficiency of system and service quality. More precisely, the most striking sources of resistance were found to be poor ergonomics and the lack of service, followed by payment concerns and uncertain data handling. As illustrated by a hierarchical value map, these attributes were related to numerous consequences. Consumers particularly lack certainty for a product decision and were afraid of upcoming financial burdens as well as imminent time effort. This mainly conflicts with the values of convenience, performance and economy and hinders the pursuit for self-actualization and material security. The results suggest more investment in the surrounding purchase environment of mobile sales rather than the products itself, but also reveal a high demand for marketing to promote the benefits of m-insurance.

STUDY 3

4 Handling the Perception of Risks through Information and Service Quality in M-Commerce

4.1 Abstract

The construct of perceived risk has long been seen as a constantly prevailing factor in technology adoption which needs to be addressed by practitioners. Recent literature has challenged this view and stated boundaries of risk (Gefen & Pavlou, 2012). One effective means to restrict risks is the employment of consumer service. Nevertheless, an overinvestment of service was found to harm the intention to transact. The present study reconsidered these assumptions for the background of a new sales channel (m-commerce) and high complexity of products (insurance). Therefore it applies a set of four statistical methods, comprising structural equation modeling, polynomial equation modeling, the response surface methodology and a between-group design. In the first step, the structural model was investigated. It is shown that privacy risk acts as a driver for performance risk which further reinforces financial, time and psychological risk. Psychological risk concentrated the impact of the other risk dimensions and acted as mediator towards purchase intention. This knowledge was further applied to refine the posited moderation of the risk-purchase association by service quality. Consistently, a moderation of quadratic (inverted-U) shape was supported, but revealed a less significant effect. We found only minor risk perceptions at the level of low and high service quality, but a high risk perception at the level of modest service quality. Moreover, it was shown that an overinvestment of service quality is more likely for low risk situations, but does not threaten the high risk situations, implying a context relatedness of the prior found moderation. The theoretical and practical implications are discussed.

4.2 Introduction

The widespread diffusion of mobile phones has accelerated the ongoing digitalization of service industries. Consequently, companies are confronted with new mobile sales approaches that require a rework of contemporary product offers. One of the major challenges is the risk that emerges when buying a product via mobile devices. This becomes even more relevant with increasing complexity of the service (e.g. insurance) that is sold (Curran & Meuter, 2005; Maity & Dass, 2014; Murray & Schlacter, 1990). In general, for such complex products consumers' have get used to "research online and purchase offline", termed as ROPO behavior (Heil et al., 2010). This behavior clearly reflects a consumer's attempt to mitigate the uncertainty during a purchase (Lo & Lie, 2008), by reducing the asymmetric information and opportunistic interests among the transaction parties (Yang et al., 2015). ROPO accordingly lowers the probability of experiencing unethical behavior of sales persons such as providing misleading information to gain higher commission (Román & Munuera, 2005) and reduces a consumer's vulnerability (Gefen & Pavlou, 2012). To shed another light on this, industries such as insurance have not yet mastered how to manage this uncertainty nor how to provide sufficient assurance and convenience during the research online to support a direct contractual conclusion. This makes a purchase offline indispensable for consumers (Meuter, Ostrom, Roundtree, & Bitner, 2000; Murray & Schlacter, 1990).

Regarding this dilemma, research lacks a thorough investigation of the perceived risks (PR) that arise from complex online transactions (Lim, 2003). This can be attributed to several reasons, such as the discordance about the risk dimensions and their definition in different contexts (Lim, 2003). It was found that the diverse dimensions of risk are not equivalent constructs on the same level, but rather show substantial interdependencies. Scholars accordingly argued that performance risk is the source of all other risks (Cunningham, 1967; Keh & Pang, 2010), while these in turn are finally concentrated in the psychological risk. Nevertheless, the majority of investigations de facto disregard the advanced structure or risk (Crespo et al., 2009; Featherman & Pavlou, 2003; Martins, Oliveira, & Popovič, 2014). In fact, in an increasingly competitive market it becomes more and more important to identify the sources of risks since it allows internet vendors to take action in the right places (Lim, 2003).

Additionally, opportunities to handle existing risks are rarely identified (Rosen & Purinton, 2004). A few studies confirmed the usefulness of service and information as a decision aid to cope with uncertainty (Nicolaou, Ibrahim, & van Heck, 2013; Sweeney et al., 1999). For example, Parasuraman et al. (2005) propose functions such as one-click ordering, trust-e symbols, and search engines as key cues to instill service quality (SQ). Similarly, Ranganathan and Ganapathy (2002) suggest various features including product samples in the form of movie-clippings, navigational tools, product-price comparisons, email, FAQs or certificates. Montoya-Weiss et al. (2003) found a positive association of SQ and online channel usage. However, to the authors' knowledge, research has not yet investigated the potential of such consumer services to undermine risks in the market of complex products and m-commerce. Related findings by Gefen and Pavlou (2012) revealed a curvilinear moderation of the effect of risk on transaction intention by the perceived effectiveness of the institutional structures (PEIS). Admittedly, this effect challenged the view on the vast majority of linear effects in information system (IS) research and calls for a reinvestigation of present findings. This is supported by various findings that revealed ambiguous results, ranging from a positive relation (Wu & Wang, 2005) to no relation (Gupta & Kim, 2010) to a moderate negative relation (Luo, Li, Zhang, & Shim, 2010; Nicolaou et al., 2013) up to a strong negative relation (Grewal et al., 2007) between risk and purchase intention.

To address these issues, this article follows and combines two strings of research: In the first instance our research aims at investigating the internal structure risks in m-commerce and secondly clarifies the potential of service and information quality (IQ) in order to handle the risks. To obtain accurate knowledge about the structure and interplay of the mentioned variables, we applied four statistical approaches: Firstly, we used a structural equation approach and extended our findings with polynomial equation modeling and the RSM. This allowed us to not only deduce insights about the multivariate regressions in our model, but also to gain insights about the higher-order polynomial structure of risk and SQ (Edwards, 2002). Finally, we translated these theoretical thoughts into a between-group design, to gather insights about the effectiveness of SQ in reducing risks in a concrete realization of an app.

This provides four major contributions to the recent IS literature: Firstly, our study clarifies the interdependencies of risk in an uncertain purchase environment. This enhances the disunity about the dimensional structure of different facets of risk in the m-commerce (Lim, 2003) and provides future guidelines towards a more accurate investigation of risk in the IS research (Featherman & Hajli, 2015). Secondly, our model examines the role of service and IQ as a means to overcoming given obstacles in m-commerce as depicted by the risk concept. In conclusion of the first two points, our investigations pinpoint a thorough understanding of the processes that consumers undergo in their decision process. As demanded (Lim, 2003; Pavlou, 2003; Ranganathan & Ganapathy, 2002) this allows scholars and practitioners to understand the attributes of SQ that shape a convenient decision and enables an accurate usage of SQ to enhance the product encounter. Thirdly, our finding challenges the generalizability of recent findings about the boundaries of risk in online transactions by Gefen and Pavlou (2012), by investigating a different online marketplace, a different online medium, a different product in a different contact phase and different scales. This finally extends the applicability of the previous findings to the broad literature of SQ and gives rise to rethinking existing findings about the association of risk and behavioral intention. Lastly, our study provides orientation for a comprehensive methodological approach by applying a set of four methods to obtain an elaborated view on the risk SQ association.

The remainder of this paper reads as follows: We start with a review of the literature in section 1. In section 2 we derive a conceptual frame, including our research model and the according hypotheses. Next, we explain the chosen methodology, followed by the analyzation of the results in section 3 and 4. Finally, we discuss our results in the light of theory and practice and conclude implication for the future research in section 5.

4.3 Theoretical Background

4.3.1 Perceived Risk Theory.

The construct of PR has produced considerable research interest since its introduction in the literature (Bauer, 1960). In the classical decision theory PR is defined as the decision process, in consequence of which possible outcomes, probabilities and the subjective value of the decision are assessed (Arrow, 1965; Pratt, 1964). Later, scholars more specifically described PR as a combination of two factors, divided into the probability of a potential loss ("chance") as a consequence of a decision and the value ("danger") ascribed to this loss (Cox, 1967; Cunningham, 1967; Kogan & Wallach, 1964; Peter & Tarpey, 1975). Recently, for Kim, Ferrin, and Rao (2008) PR denotes a consumer's uncertainty about potential negative consequences resulting from off- and online-transactions. Thereby, the general notion of "negative consequences" obtains the highest compatibility for the multiple dimensions of risk that are existent in m-commerce. This multidimensional nature was stated repeatedly by a great body of literature (Forsythe, Liu, Shannon, & Gardner, 2006; Forsythe & Shi, 2003; Jacoby & Kaplan, 1972; Kaplan, Szybillo, & Jacoby, 1974; Lim, 2003; Peter & Ryan, 1976). For instance, Featherman and Pavlou (2003) empirically analyzed the effects of seven facets of PR on e-service adoption. A general consensus for the classification of PR exists for the dimensions performance, financial, time and psychological risk (Kim et al., 2008; Lim, 2003). Additionally, in the digital contexts privacy risk has been found to enhance the predictive value of risk (Crespo et al., 2009; Featherman & Pavlou, 2003; Lee, 2009; Luo et al., 2010). Further dimensions of risk such as social and physical risk only revealed limited evidence regarding their effect on technology adoption and are thus deemed to play a minor role for m-commerce (Crespo et al., 2009; Featherman & Pavlou, 2003; Lee, 2009). The following conceptual framework will thus be concentrated on the five predominant dimensions.

4.3.2 Mobile Service Quality.

The concept of SQ has established as pivotal aspect of IS success (Delone & McLean, 2003). A common notion was proposed by Zeithaml et al. (2002, p. 358), who defined e-service-quality as “the extent to which a website facilitates efficient and effective shopping, purchasing, and delivering of products and services”. Its assessment arises from the comparison of the service a company should offer (i.e. expectation) and its actual service performance (Parasuraman et al., 2005). Apparently, the nature of service is changing continuously along with the technological advancement. Contemporary approaches thus distinguish two forms of service: Traditional face-to-face service and the increasing face-to-screen service (Cai & Jun, 2003; Froehle, 2006). The latter is characterized by service that is either mediated through technology or entirely generated by the technology. Parasuraman et al. (2005) hereto describes the emergence of the SQ perception as a process triggered by service cues in an IS. Those perceptual attributes coalesce to an evaluation along more abstract dimensions. With increasing IS experience, this implies that consumers can quickly identify the service cornerstones of a sales environment and can easily appraise the quality of the service (Chen & Dubinsky, 2003; Griffith & Krampf, 1998). For technology-mediated service those cues can appear in the form of hotlines, email or live chat functions, while technology-generated service refers to features such as FAQs, navigational tools (i.e. search engines) or test seals (Froehle, 2006; Ranganathan & Ganapathy, 2002). Taken together, SQ in m-commerce emerges as a result of the service cues that are provided. Over recent decades, various measurement models have been provided to characterize the construct of service performance. An early approach undertaken by Parasuraman, Zeithaml and Berrey (1991; 1988) revealed a five-dimensional scale called SERVQUAL which incorporates the facets of reliability, responsiveness, assurance, empathy, and tangibles. Generally, the construct rendered robust outcomes in IS contexts regarding its reliability and construct validity (Fisk, Brown, & Bitner, 1993; Jiang, Klein, & Carr, 2002; Pitt, Watson, & Kavan, 1995), but was also controversially discussed in light of its dimensional distinctiveness (Gefen, 2002). Nevertheless, the five dimensions of the basic SERVQUAL persist as reliable indicators. Its high levels of reliability and validity (content, convergent, discriminant, nomological) across different businesses and cultures, combined with its economy, provides ideal conditions for IS research (Pitt et al., 1995) and is thus referred to in this article.

4.3.3 Mobile Information Quality.

Mobile IQ can be defined as the performance of a system in providing information (Zheng et al., 2013) and comprises all provided material that appears in an m-commerce setting (i.e. an app; Montoya-Weiss et al., 2003). Therefore, m-commerce that provides high IQ should render all information needed to make a well-informed decision (Broekhuizen, 2006; Montoya-Weiss et al., 2003). This typically includes information aspects concerning both the product and the process such as price, payment options, corporate policies and conditions and public relations. In the literature the concept of IQ is widely defined by the dimensions of information accuracy, comprehensiveness/ease of understanding, reliability, completeness, relevance, degree to which information is up to date, timeliness and format adequacy (Ahn et al., 2007; Delone & McLean, 2003; Doll & Torkzadeh, 1988; Liang & Chen, 2009; Palmer, 2002; Rai et al., 2002). According to Lee, Strong, Kahn, and Wang (2002) these dimensions coalesce to an intrinsic, context-based, representational and accessibility category. Applied to the above dimensions the intrinsic view captures the inherent quality of the information, the context-based view refers to the usefulness for specific tasks, the representational view refers to the format, and accessibility covers how accessible information is with respect to privacy and security. Altogether, these dimensions enable a comprehensive view on IQ (Lee et al., 2002). Similar to SQ, it can be assumed that the perception of information quality in m-commerce basically arises from the information cues that are provided, such as the information format, amount of text or the accentuations and wrap-up of key information. Lala, Arnold, Sutton, and Guan (2002) likewise argue that consumers build their impression about quality measures through surrogates such as brand name and reputation. Accordingly, the authors applied assurance seals as an indicator of different amounts of IQ. This is supported by Nah and Davis (2002), who stressed that consumers would rather scan websites sporadically instead of reading the details. In the past, literature has shown that the quality of the information in an IS is pivotal to making good purchasing decisions and IS success (Kim et al., 2008; Kuan, Bock, & Vathanophas, 2008; Palmer, 2002). Accordingly, the value of IQ is constantly increasing due to higher consumer uncertainty, demands and vendor competition in online markets (Chen & Dubinsky, 2003).

4.4 Research Model and Hypotheses Development

4.4.1 Risk Interdependencies.

The development of attitudes towards products and channels arises from concrete perceptual cues or the lack of these cues throughout a product encounter (Parasuraman et al., 2005). This aspect provides plausibility for an iterative evolvement of risks initiated by concrete cues (small font) to more abstract attributes (poor ergonomics) leading to higher order abstractions (higher handling effort, inconvenience). This so called means-end chain corresponds with Keh and Sun's (2008) differentiation in non-personal and personal risks. The first comprises risks that are directly triggered by external cues such as data loss, product failure, additional payments and search effort, while the latter denotes a solely internal risk deriving from the assessment of the antecedent non-personal risks. The perception of privacy risk, capturing the potential loss of control over personal information (Featherman & Pavlou, 2003), is closely related to perceptual cues like e-trust seals, brand name and other service cues conveying integrity of a company (Özpolat, Gao, Jank, & Viswanathan, 2013; Özpolat & Jank, 2015). The close relatedness of privacy risk to initial perceptual cues makes it a predictor for further non-personal risks such as the accurate functioning of the product. In turn, a high privacy risk negatively influences the perception of the performance of the product inducing a higher probability of product malfunctioning, theorized in the concept of *performance risk* (Jacoby & Kaplan, 1972; Stone & Grønhaug, 1993). The complexity of insurance, including various terms, conditions and possible combinations further drive the opportunity to oversee or misunderstand details, which can result in poor decisions (Black et al., 2002; Loewenstein, 1999). Consequently, a consumers estimation of performance risk increases with higher levels of product complexity. A high amount of performance risk can therefore produce potential following extra-costs due to product failures and remedy of such failures (Jacoby & Kaplan, 1972). This pushes the possibility of a monetary loss, defined as *financial risk* (Stone & Grønhaug, 1993). Along with this risk of product malfunctioning and financial loss, consumers are impelled to increase their time investment to assure an accurate functioning and avoid later product issues (Kim et al., 2008). This potential loss of time is denoted as *time risk* (Jacoby & Kaplan, 1972). Kim et al. (2008) even outline time to be a part of the financial risk. Finally, the emerging extra-effort triggered by higher performance, financial and time risk causes feelings of tension, discomfort, anxiety and avoidance behavior turning into mental stress, which form the central characteristics of *psychological risk* (Broekhuizen &

Jager, 2004; Crespo et al., 2009; Featherman & Pavlou, 2003; Lim, 2003). It can be assigned to the aforementioned abstract personal risk.

The proposed associations are supported by Cunningham (1967), who set performance risk as the source of all other involved risks except for the newer privacy risk. Keh and Pang (2010) demonstrate that the performance risk acts as a strong predictor for psychological risk. Stone and Grønhaug (1993) further argue that lastly a consumer`s psyche translates any risk into discomfort. Accordingly, psychological risk was found to mediate the relation between several other risk dimensions and a more general estimation termed as overall risk (Stone & Grønhaug, 1993). Furthermore, an abundance of studies have supported a negative influence of several risk dimensions on the willingness to transact (e.g. Gefen & Pavlou, 2012; Jarvenpaa & Todd, 1996; Liébana-Cabanillas et al., 2014; Pavlou, 2003; Sweeney et al., 1999; Yang et al., 2012). A meta-analysis by Zhang et al. (2012) emphasized the role of perceived risk as predictor for behavioral intention. We therefore conclude that psychological risk acts as the central intermediary between the antecedent risk dimensions and intention to purchase a product. An overview of the proposed path can be found in Figure 4.1. Finally, the following hypotheses are stated:

H1: Consumers' perceived privacy risk negatively affects the perception of performance risk.

H2: Consumers' perceived performance risk negatively affects the perception of financial (a), time risk (b) and psychological risk (c).

H3: Consumers' perceived financial risk negatively affects the perception of time risk.

H4: The perceived psychological risk is next to performance risk (cf. H2) positively predicted by the privacy (a), financial (b) and time risk (c) and has a negative impact on purchase intention (d). It further mediates the relation between the four risks and purchase intention (e).

4.4.2 Service Quality and Information Quality.

Recent findings about the interplay of SQ and IQ have produced ambiguous results. More precisely, the information construct has often been put under the umbrella of service performance (Ding, Hu, & Sheng, 2011), but was also often conceptualized as equivalent construct next to SQ in order to predict website quality (Delone & McLean, 2003). Pearson, Tadisina, and Griffin (2012) found a mediating role of IQ for the association between SQ and perceived value. In contrast, former results in online channel investigations saw information as antecedent to high SQ (Alba et al., 1997; Montoya-Weiss et al., 2003; Swaminathan, Lepkowska-White, & Rao, 1999). As mentioned earlier, in today´s e- and m-commerce environments, quality assessments initially arise from the exposure to service and information cues (Grewal et al., 2007; Parasuraman et al., 2005). The digital nature hereby induces a predefined order of exposure, meaning that concrete information cues are hidden behind service cues (e.g. search boxes, FAQ and info buttons, clickable guarantee and security icons etc.). Therefore, the evaluation of SQ arises in an earlier stage and provides consumers with an indication of the quality of information based on prior experiences and the perceived effectiveness of the provider structures such as those derived from a rich and qualitative service (Gefen & Pavlou, 2012). A rich service should therefore instill a high IQ as it provides common access points to retrieve certain information (Pearson et al., 2012) and mirrors the institutional structures. In sum, this leads to the following assumption:

H5: Higher values of SQ lead to higher values in the IQ,

4.4.3 Service Quality, Risk and Purchase Intention.

Few studies have examined the association of SQ and perceived risk in electronic markets. Prior findings mainly state a positive impact of service on risk perception. In detail, this can be explained by several mechanisms: Dowling and Staelin (1994) acknowledged that insufficient knowledge is an antecedent for risk perception. However, shopping online can provide numerous decision aids such as price comparisons, reviews or product details. These service cues provide information which fills consumers' knowledge gaps and broadens their understanding of the product. This better understanding then reduces uncertainty (Luhmann, 1979; Sweeney et al., 1999). Ding et al. (2010) likewise demonstrated that users felt more skillful in using a website through SQ. SQ thus helps to improve the quality of decisions and alleviates the risk of product malfunctioning (Ranganathan & Ganapathy, 2002), captured in performance risk and further related to financial risk. Ubiquitous access towards service support allows consumers to instantly solve their queries and enable a quick decision. It was thus pointed out that lowered search costs introduced by navigational tools are a fundamental benefit of electronic marketplaces (Ranganathan & Ganapathy, 2002). SQ therefore counteracts an impending high search effort and lowers time risk. It further imparts control, convenience and assurance (Collier & Kimes, 2012; Collier & Sherrell, 2010; Ding et al., 2007). This finally creates more trust and relieves consumers of psychological risks (Pavlou, 2003; Zhou & Lu, 2011). Consequently, the following hypothesis can be stated:

H6: SQ is negatively associated to privacy (a), performance (b), financial (c) and psychological (d) risk.

In support of the significance of SQ, it was among others found to impact ease of use, trust, perceived value, usefulness, loyalty, consumer satisfaction and playfulness. In the IS literature these are common predictors of behavioral intention. The association between SQ and behavioral intention was thus repeatedly confirmed in the literature (Ahn et al., 2007; Carlson & O'Cass, 2011; Kaur & Gupta, 2012; Mulki, Jaramillo, & Carrillat, 2009; Pearson et al., 2012; Sweeney et al., 1999; Zhou & Lu, 2011). This leads to the following hypotheses:

H 7: SQ positively influences the purchase intention.

4.4.4 Information Quality, Risk and Purchase Intention.

Retailers can enhance consumers’ satisfaction during a purchase process by providing them with all information that would be tedious to obtain otherwise (Delone & McLean, 2003). Nicolaou et al. (2013) argue that IQ increases the transparency of products and helps to detect abnormalities, which thus mitigates performance risk. The availability of information also induces a self-controlled utilization of information. This fosters good decisions by improving consumers´ ability of integrating, remembering and using information (Lynch Jr & Ariely, 2000) and makes them more skillful (Ding et al., 2010). In turn, a high IQ reduces the error probability in terms of performance, privacy and financial loss for the decision making (Broekhuizen & Jager, 2004). Furthermore, by providing well-organized information (i.e. accurate, complete, timely, comprehensive, reliable and relevant) concerns about the search and information-processing such as wasting time can be reduced (Zheng et al., 2013). Consistent with this, findings supported the positive impact of IQ on search and information-processing costs (Broekhuizen, 2006; Gu, Konana, Rajagopalan, & Chen, 2007; Lynch Jr & Ariely, 2000). In contrast, a lack of information has been named as a central source for uncertainty (Daft & Lengel, 1986; Littler & Melanthiou, 2006). It can therefore be assumed that an increased IQ leads to reduced uncertainties concerning privacy, performance and financial loss during the contractual conclusion in m-commerce. Concerns and discomfort with the decision consequently decrease and attenuate psychological risks (Broekhuizen & Jager, 2004). This leads to the following assumption:

H8: IQ is negatively associated to privacy (a), performance (b), financial (c) and psychological (d) risk.

IQ is known as a success factor for technology acceptance, leading to higher intentions to purchase, to revisit and to repurchase from a website (Ahn et al., 2007; Kuan et al., 2008; Tao, 2008). A high IQ improves vendors' reliability, trustworthiness and forms a convenient purchase experience (Chen & Dubinsky, 2003; Kim et al., 2008; Nicolaou et al., 2013). This finally gives consumers the confidence to engage in a mobile purchase and was found to induce consumer satisfaction, loyalty and trust (Delone & McLean, 2003; Nicolaou et al., 2013; Pearson et al., 2012). However, it is noteworthy that only useful and valuable information is assumed to be relevant from a costumer's point of view (Chen & Dubinsky, 2003). By taking previous findings into account, the following hypothesis is concluded:

H9: IQ positively influences the purchase intention.

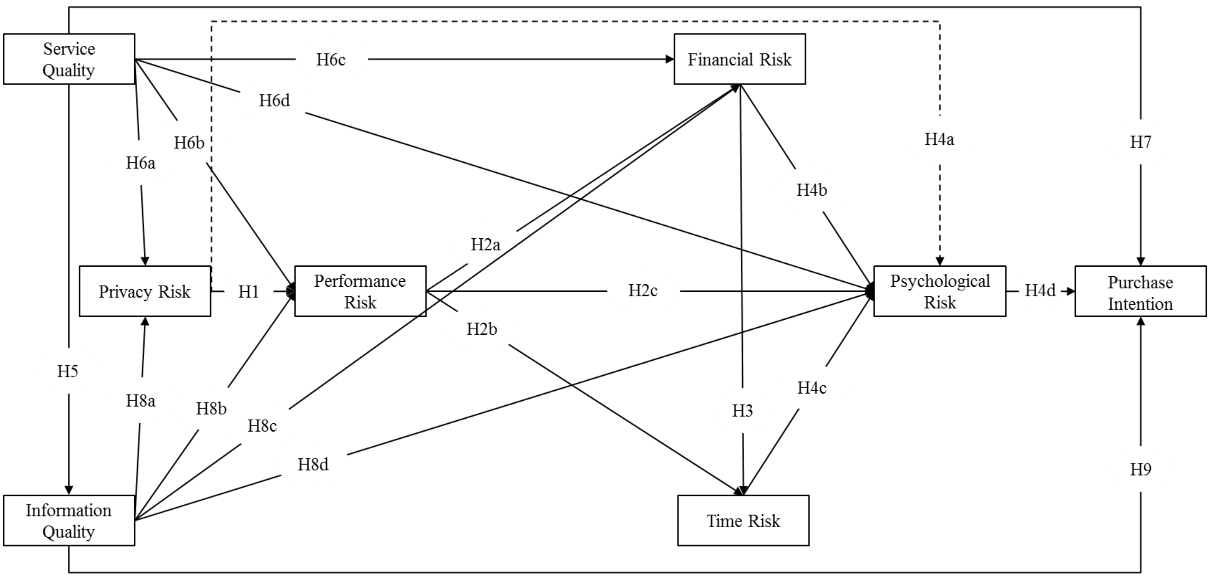

Figure 4.1 Hypothesized structural equation model.

4.4.5 Polynomial Effect of Risk on Purchase Intention.

The oversimplification of linear models has recently been criticized, accompanied by a demand for more accurate investigations of the complex nature of digital commerce (Brown et al., 2012; Edwards, 2002; Gefen & Pavlou, 2012). Similarly, Gefen and Pavlou (2012) explored the boundaries of the effect of risk on the intention to transact. They delineated a quadratic moderation of the risk to transaction intention linkage by the perceived effectiveness of the institutional structures (PEIS). PEIS is defined as "buyers believe that appropriate conditions are in place to facilitate transactions with sellers" (Gefen & Pavlou, 2012, p. 941). Similar to SQ, it is determined by feedback mechanisms, perceived effectiveness of escrow service and credit card guarantees. The results suggest that risk becomes irrelevant in the case of high or low PEIS and has the highest impact under modest PEIS. Risk thus delineates a nonlinear effect on transaction intention with three extreme manifestations. Referring to Dowling and Staelin's model (1994), under conditions of high uncertainty and vulnerability, risk becomes irrelevant since the probability of high losses inhibits the willingness to purchase a product. This equals the situation of low SQ and results in the a-priori preclusion of the transaction (Point 1 - No Impact). Otherwise, in case of a high SQ, doubts about a product malfunctioning or financial loss as well as search effort are minimized through the decision aids that are presented. In consequence, risk plays a minor role, too (Poon, 2008). Modest levels of SQ can illustratively be described as a condition of sciolism, which is related to high confusion and uncertainty and causes a maximum of risk influence. However, Gefen and Pavlou (2012) examined the perceived effectiveness for very common and effective platforms (eBay and Amazon). Referring to these, many people possess routines regarding their decision behavior, meaning that products are bought without high cognitive investment after the adoption has taken place. Conversely, an initial adoption of m-commerce is marked by higher risks and thus higher need for cognition. This is even more relevant for complex products. We thus expect mobile devices in the combination with highly complex products to not obtain sufficient assurance through SQ to preclude risk from the purchase decision.

Our assumptions are supported by recent theorizing from Özpolat et al. (2013), who found that higher amounts of assurance seals (cf. SQ) are of positive value in situations of higher uncertainty (small seller size, shopper newness and final stage of purchase), but can harm the purchase completion rate in less uncertain situations. In turn, while Gefen and Pavlou (2012) argue that a high level of PEIS harm the purchase intention, we claim that in high-risk situations the principle of "the more SQ, the better" pertains. In line with previous studies (Dowling & Staelin, 1994; Gefen & Pavlou, 2012) a modest SQ will maximize the influence of risk on a buyers' decision to engage in mobile purchases (Point 3 - Maximum Impact). Finally, this leads to the following hypothesis:

H10: The negative effect of risk on purchase intention reveals a weak impact under conditions of high SQ and a substantial impact under moderate levels of SQ, but disappears under the condition of low SQ. Thus, SQ moderates the effect of risk on purchase intention in a quadratic fashion.

It is noteworthy that equivalent effects can be assumed for IQ due to its high interdependence to SQ and its comparable impact on the included variables. However, in this study we focused mainly on SQ in order to keep the content lucid, but also examined the quadratic moderating role of IQ and SQ with all five risk dimensions in an additional explorative analysis.

4.5 Research Methodology

4.5.1 Design and Procedure.

The data were gathered by an online survey between October 2013 and July 2014. The survey consisted of two parts; an initial service treatment and a subsequent questionnaire. A short introduction text was presented initially to create a common travel mindset, within which all participants imagined an immediately imminent journey. As a target we chose a European city with given relevance to insurance covering under consideration of criminality reports. In this context the participants were encouraged to make use of a new app. For this purpose, we adapted an already launched insurance app in order to create a realistic scenario. Next to the provision of several travel assistance features, this app enabled people to purchase travel insurance anywhere and anytime via a mobile device. The insurance covered health, costs arising through misuse of one`s own smartphone (i.e. in case of theft) and the loss of important travel documents and bank cards. The policy covered a maximum 30 days, with a daily price of 90 cents. Participants were visually guided through the app by presenting a sequence of in-app screenshots. These were based on the logical order during a purchase process and finished by showing the option to conclude the contract. Hereby, a forced decision was not intended, so that the participants finished the introduction by clicking the general “continue”-button. Since individual experience of a brand is known to alternate consumers’ perception (Ruparelia, White, & Hughes, 2010), we removed all existing brand labels and assigned an invented name, to avoid biases through prior experiences.

Our treatment consisted of two conditions, constituting either a high SQ (HSQ) or low SQ (LSQ) by randomly alternating the service richness of the presented screenshots. In general, service richness in m-commerce is understood as the availability of service approaches; for example, by providing a telephone number or info buttons (Chen & Dubinsky, 2003; Griffith & Krampf, 1998). Based on the assumption of a common understanding of service symbols, the mere availability of service features is sufficient to enhance consumers’ SQ perception. In the HSQ condition, we thus augmented screenshots of the original app by implementing six service features with common symbols, and explained these features in a side box. The features consisted of an agent helpline button, a FAQ-button, a test seal, a privacy assurance seal, several info buttons with product-related explanations and app handling information boxes. In contrast, the LSQ condition showed a blank version of the app, free of additional features. To control for the effectiveness of our treatment, we added two control items to the questionnaire in direct subsequence to the app introduction. The first dichotomous item asked the participants whether they had noticed support or service functions while using the app. In the service condition 50.8% responded that they had noticed the service functions compared with 41.1% in the blank condition. A t-test revealed a significant difference between both conditions (t = 2.68; p < .01). In a second question we asked for the number of service functions that had been noticed. Those participants using the service condition noticed an amount of 2.13 functions on average, while people in the blank condition noticed just 1.74 functions. This difference was significant on a 5% α-level (t = -2.37). The manipulation check therefore conclusively confirmed the effectiveness of our treatment. In the final step, the online questionnaire had to be answered.

A pre-test consisting of 15 research employees and students had previously been conducted to guarantee an appropriate comprehension of questions. Therefore, the participants initially answered the questionnaire and were interviewed afterwards with regard to remaining ambiguities. Finally, all found issues were fixed.

4.5.2 Sample.

The majority of participants for this study were recruited by an email circular sent to students at the Konstanz University of Applied Sciences (HTWG)[9]. In addition, we used online platforms, blogs, forums and social networks to recruit participants. As an incentive to participate, we offered participants the opportunity to win three Amazon vouchers to the total value of €60. In total, 791 out of 3,061 visitors completed the questionnaire - a response rate of 25.8%. There were no missing values in the data set due to a forced choice format of the items. Prior to the data analysis, we filtered all duplicates (by checking IP, email addresses and age). Twenty-nine cases had to be excluded from further analyses, leading to a remaining data set of 762 participants. The LSQ and HSQ conditions were assigned 384 and 378 respondents respectively. The sample demographics are summarized in Table 4.1.

[9] The data evaluation of this study was partly conducted together with Petra Lederle in context of her bachelor thesis, which was supervised by me.

Table 4.1 *Profile of Respondents.*

Measure	Item	Frequency	Percentage (%)
Total		762	100
Gender	Male	330	55.6
	Female	424	43.3
Age	< 20	128	16.8
	20-29	465	61.0
	30-39	101	13.3
	> 39	68	8.9
Education	No schooling completed	15	2.0
	Lower secondary school	24	3.1
	Middle secondary school	110	14.4
	Higher secondary school	411	53.9
	(Under-) Graduates	202	26.5
Income in €	< 1001	473	62.1
	1001-2000	134	17.6
	2001 – 3000	83	10.9
	3001 – 4000	39	5.1
	4001 – 5000	15	2.0
	> 5000	18	2.4
Smartphone Ownership	Yes	656	86.1
	No	106	13.9
Travel Insurance Ownership	Yes	379	49.7
	No	383	50.3
Interested in Travel Insurance	Yes	373	49.0
	No	389	51.0
Intention to Buy Travel Insurance	Yes	26	3.4
	No	736	96.6
Used Device for Study Participation	Smartphone	97	12.7
	Tablet	41	5.4
	PC / Notebook	624	81.9
Mobile Device Expertise	Mean[a]	4.41	
Insurance Expertise	Mean[a]	3.24	

Notes. [a]Experience was measured by using four items from Jaiswal et al. (2010) on a 7-Likert scale with either focusing on the mobile device or insurance, respectively.

Fifty-six percent of the respondents were female, compared to 43% males. The average age was 26.52 years (*SD* = 9.72), with the largest group between 20 and 29 (61%). The majority of respondents had completed secondary education (54%), followed by graduates (college; 27%) and middle secondary education (14%). Sixty-two percent of the participants had an income below €1,001 per month, and 18% earned more than €1,000, but less than €2,001. The remaining 20% earned more than €2,001. Finally, it can be presumed that the majority of respondents had a student background, which constitutes an adequate sample for evaluations in m-commerce due to given familiarity with internet communication technology. We also controlled for smartphone ownership, insurance ownership and existing interest in insurance. A group comparison under usage of t-tests for independent samples revealed no significant differences between the two conditions regarding all demographical and control variables.

4.5.3 Measures.

The principle constructs were based on existing measures and partly adapted to suit the specific usage context in which they were applied. All responses were based on a 1-7 Likert-type scale ranging from 1 for ”strongly disagree” up to 7 for “strongly agree”. We measured SQ by selecting four items obtained from Wang and Tang (2003), in a short-version introduced by Wang (2008). This scale was adjusted to e-commerce purposes and stems from the widespread SERVQUAL-Scale by Parasuraman et al. (1988). It measures the four dimensions of SQ: responsiveness, reliability, assurance and empathy. Each dimension is represented by one item. The applied measure further disregards the dimension of tangibles (e.g. navigation, aesthetics) as it places a strong focus on the engineering-oriented attributes of m-commerce, which are not addressed in this study. To measure IQ we used a four-item scale adapted from Doll and Torkzadeh (1988) representing the three dimensions: content, accuracy and timeliness of information. The five dimensions of perceived risk were measured with adapted scales of Stone and Grønhaug (1993), Jarvenpaa and Todd (1997) and Featherman and Pavlou (2003) as used by Crespo et al. (2009). Finally, we measured mobile purchase intention with two adapted items from Burton and Andrews (1996) in a modified version by Gupta et al. (2004a). All items can be seen in Appendix 8.4.

4.5.4 Model Fit.

Prior to the data analysis, we assessed reliability, discriminant validity, and convergent validity of the applied constructs. To test for internal consistency Cronbach´s alpha and the item-to-total correlation were observed. For all implemented scales, the recommended α-value of .70 (Nunnally, 1978) was exceeded. The item-to-total correlation ranged between .58 and .89, what is within given boundaries (Nunnally & Bernstein, 1994).

In the next step, we built a SEM to assess the validity and model fit. Convergent validity was controlled for by evaluating the factor loadings, the average variance extracted

(AVE) and composite reliability (CR). All factor loadings were significant (λ = .62 - .97) within recommended thresholds (Hair et al., 2013), suggesting at least values above .50 and ideally above .70. The AVE ranged between .63 and .83, which is above the recommended value of .50 (Fornell & Larcker, 1981). Finally, the CR ranged from .84 to .94, and accordingly surpassed the given threshold of .70 (Hair et al., 2013). Discriminant validity was tested by comparing the square root of the AVE with all correlations between the respective variable and all other variables. The values exceeded the correlations in every case, thus adequate discriminant validity could be confirmed. A summary of all values is given in the Appendix 8.8 *Reliability, Validity and Model Fit.*Appendix 8.3. Finally, we compared fit indices obtained through a confirmatory factor analysis to recommended thresholds to control the model's goodness-of-fit (Ostrom & Iacobucci, 1995). These are values below 3 for the ratio between χ^2 and the degrees of freedom, values above .90 for the GFI, above .95 for the CFI and TLI and values below .05 for RMSEA and SRMR. Finally, the hypothesized model revealed a satisfactory fit (χ^2/df = 2.78; GFI = .91; CFI = .96, TLI = .95, RMSEA = .048, SRMR = .040). Overall, our data demonstrated robustness and adequacy for further analyses.

To prevent interpretation biases, we further controlled for multi-collinearity, multivariate normal distribution, homoscedasticity and linearity, as recommended in the literature (e.g. Hair et al., 2013; Podsakoff et al., 2003). The highest variance inflation factor in our data was 2.5, which is uncritical to multi-collinearity (Ostrom & Iacobucci, 1995). The values for skewness and kurtosis ranged between -0.64 and 0.81 as well as between -0.31 and -1.28, providing evidence for normal distribution according to the critical values of 2 for skewness and 7 for kurtosis (West, Finch, & Curran, 1995). Homoscedasticity and linearity were graphically tested by observing the scatterplots, without detecting major issues.

4.5.5 Common Method Bias.

The Common Method Bias (CMB) was tested by applying Harman`s Single Factor Test in combination with a Marker Variable Test. CMB can be seen as a serious threat when more than 50% of the variance over all items is explained by one latent factor. Since constructs in a hypothesized structural equation modeling (SEM) are commonly interrelated, entering a seemingly non-related marker variable is recommended in order to separate the common method variance. For this purpose we included a variable measuring the involvement in the implemented service features. In total, a single factor according to Harman explained 38.98% of the overall variance. A common latent factor further explained 22.09% of the variance, leading to no evidence for a serious common method bias.

4.6 Results

In the following we used IBM AMOS 22® software to perform structural equation modeling (SEM; Joreskog, Sorbom, & Magidson, 1979) and Matlab® to perform the polynomial regression and RSM.

4.6.1 Model Building.

To test our SEM model, we compared the hypothesized model in a first step with theoretical competing models (Hair et al., 2013). In our investigations we also incorporated several control variables. These were: age, gender, income, education, smartphone ownership, travel insurance ownership, interest in travel insurance, the assigned condition, and the device which was used for the participation (Smartphone, Tablet, PC). In Model 1 we specified no interdependencies between the independent variables and let them equally load on purchase intention. Model 2 was extended by inclusion of the loading between SQ and IQ and further between SQ, IQ and the risk dimensions in Model 3, while the loadings from Model 1 on purchase intention were kept constant. In Model 4 we set performance risk as a superior predictor for all subsequent risk dimensions. Following this, in Model 5, we added psychological risk as the bundling variable, predicted by all other risk facets, but kept all relations between the risk dimensions and purchase intention. In Model 6 we deleted remaining direct paths between the risk dimensions and purchase intention except for psychological risk, which finally corresponds to our prior hypothesized model. The results show that Model 5 and 6 reveal the best model fit with significant difference in the χ^2 values compared to all previous models (see Model 6) additionally renders a smaller BIC and CAIC value, due to less complexity. Thus, Model 6 exhibits the highest plausibility, supporting our hypothesized model. Subsequently, we tested the hypothesized interrelations and mediations. To test the latter, we applied the bias-corrected bootstrap method using 500 bootstrap samples to test for indirect effects between two variables and a mediator. In general, this method has been found to obtain robust results and is commonly suggested by the literature (Cheung & Lau, 2008; Lau & Cheung, 2012; MacKinnon et al., 2004).

4.6.2 Structural Equation Modeling.

First, we stated a positive impact of privacy risk on performance risk in H1. This hypothesis was confirmed by the data ($\beta_{\text{PrivR-PerfR}} = .60$; $p < .01$). As further assumed in hypothesis H2, performance risk acted as a predictor for financial risk and psychological risk, but did not reveal a significant direct effect on time risk ($\beta_{\text{PerfR-TimeR}} = .14$; $p = .23$, $\beta_{\text{PerfR-FinR}} = .66$; $p <$

.01, $\beta_{PerfR\text{-}PsyR} = .72$; $p < .01$). However, performance risk had an indirect effect on time risk $\beta_{PerfR\text{-}FinR\text{-}TimeR} = .31$, *CI95*[.23,.41], $p < .01$]. Furthermore, financial risk was hypothesized to predict time risk as captured by H3. This was supported with $\beta_{FinR\text{-}TimeR} = .46$ ($p < .01$). We also expected psychological risk to concentrate all previous risk dimensions, in the way of being positively predicted by privacy, time and financial risk next to performance risk in hypothesis H4. In contrast, we only found a significant positive loading for performance risk and a marginal significant loading for time risk ($\beta_{PerfR\text{-}PsyR} = .72$; $p < .01$, $\beta_{TimeR\text{-}PsyR} = .06$; $p = .07$), as well as a marginal indirect effect of financial risk on psychological risk via its effect on time risk ($\beta_{Fin\text{-}Time\text{-}PsyR} = .03$, *CI95*[.00,.06], $p = .08$). Privacy risk indirectly predicted psychological risk ($\beta_{PrivR\text{-}Med\text{-}PsyR} = .46$, *CI95*[.40,.52], $p < .01$). Furthermore, in H4, we hypothesized a mediating effect of psychological risk between all previous risks and purchase intention. For the mediation tests, we set all risks equally next to each other, without interrelations among them and no predicting paths from SQ and IQ in order to prevent the mediation effects from being induced by the indirect effect of those predicting variables. Firstly, as hypothesized in H4d we found a substantial negative direct effect of psychological risk on purchase intention ($\beta_{PsyR\text{-}PI} = .38$; $p < .01$). We subsequently found a significant mediation for performance risk and privacy risk ($\beta_{PerfR\text{-}PsyR\text{-}PI} = -.25$, *CI95*[-.37,-.24], $p < .01$; $\beta_{PrivR\text{-}PsyR\text{-}PI} = -.05$, *CI95*[-.08,-.02], $p < .01$), but only a marginal significant mediation for financial and time risk ($\beta_{FinR\text{-}PsyR\text{-}PI} = -.04$, *CI95*[-.10,-.011], $p = .05$; $\beta_{TimeR\text{-}PsyR\text{-}PI} = -.03$, *CI95*[-.06,-.00], $p = .06$). However, the latter mediation became significant, when we removed the predicting path between performance risk and psychological risk ($\beta_{FinR\text{-}PsyR\text{-}PI} = -.13$, *CI95*[-.19,-.09], $p < .01$; $\beta_{TimeR\text{-}PsyR\text{-}PI} = -.04$, *CI95*[-.07,-.01], $p < .05$). In conclusion, psychological risk acted as a central mediator for all other risk dimensions, albeit the effect of performance risk outweighs the effects of financial and time risk on psychological risk. Therefore, the results revealed partial support for hypothesis H4. In support of hypothesis H5 the data revealed a high positive impact of SQ on IQ ($\beta_{SQ\text{-}IQ} = .75$; $p < .01$). In line with hypothesis H6 and H8 SQ and IQ had a negative loading towards each risk dimension. Primarily, we only found direct significant effects for IQ with privacy risk, performance risk and psychological risk, but no significant direct effect with financial risk ($\beta_{IQ\text{-}PrivR} = -.21$; $p < .01$, $\beta_{IQ\text{-}PerfR} = -.24$; $p < .01$, $\beta_{IQ\text{-}PsyR} = -.16$; $p < .01$; $\beta_{IQ\text{-}FinR} = .00$, $p = .88$) and no direct effects for SQ ($\beta_{SQ\text{-}PrivR} = -.11$; $p = .10$, $\beta_{SQ\text{-}PerfR} = -.07$; $p = .23$, $\beta_{SQ\text{-}FinR} = .01$; $p = .94$, $\beta_{SQ\text{-}PsyR} = .01$; $p = .84$). However, SQ indirectly influenced all risk dimensions ($\beta_{SQ\text{-}Med\text{-}PrivR} = -$

.16, *CI95*[-.25,-.08], $p < .01$, $\beta_{SQ\text{-}Med\text{-}PerfR} = -.34$, *CI95*[-.42,-.25], $p < .01$, $\beta_{SQ\text{-}Med\text{-}FinR} = -.18$, *CI95*[-.26,-.09], $p < .01$, $\beta_{SQ\text{-}Med\text{-}PsyR} = -.33$, *CI95*[-.41,-.23], $p < .01$)[10]. Additionally, IQ indirectly influenced financial risk mediated by performance risk ($\beta_{IQ\text{-}PerfR\text{-}FinR} = -.24$, *CI95*[-.32,-.18], $p < .01$).

We further theorized a positive effect of SQ and IQ on purchase intention described in H7 and H9. This was finally supported by the data in two ways. We found a positive direct effect of both variables ($\beta_{SQ} = .24$, $p < .01$; $\beta_{IQ} = .23$, $p < .01$) as well as an indirect effect mediated through the risk dimensions ($\beta_{SQ\text{-}Med\text{-}PI} = .29$, *CI95*[.23,.36], $p < .01$, $\beta_{IQ\text{-}Med\_PI} = .17$, *CI95*[.13,.23], $p < .01$). An overview of the path coefficients is given in Figure 4.2. In total, the final model explained 55.8 % of the variance of purchase intention and revealed a solid model fit ($df/\chi^2 = 2.5$, $GFI = .92$, $CFI = .96$, $RMSEA = .045$; cf. Hair et al., 2013).

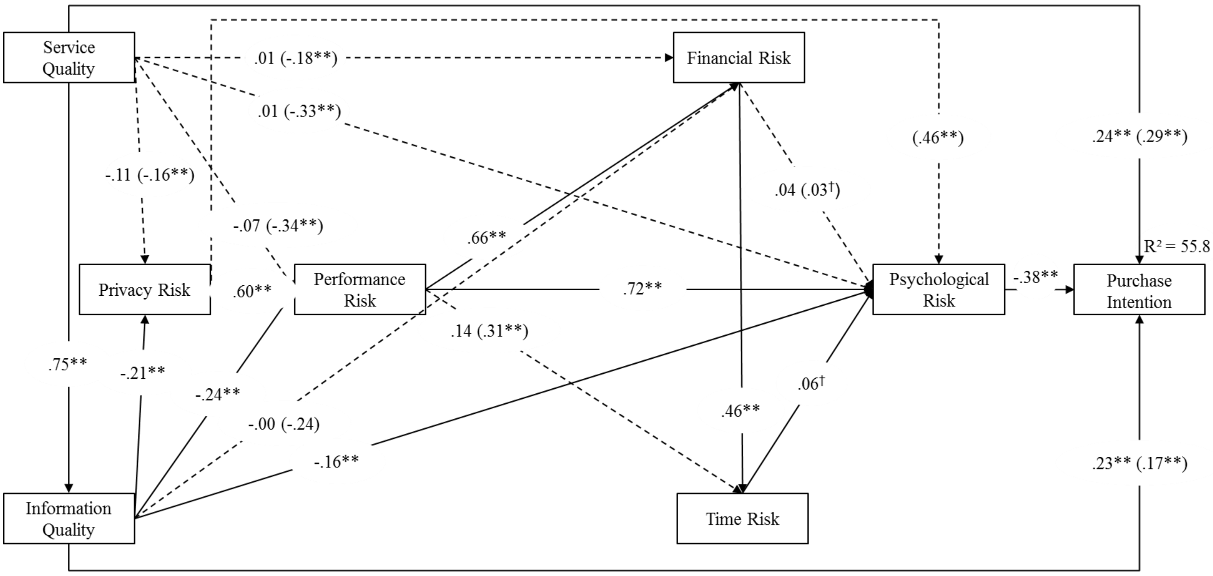

Figure 4.2 Final structural equation model. The graph shows the standardized direct and indirect effects. Dashed path are mediated (indirect) paths. Numbers in brackets refer to the standardized indirect effect. † = .1, *p < .05, **p < .01.

4.6.3 Polynomial Equation Modeling

To test the further hypotheses, we applied a confirmatory polynomial regression approach, which allows the examination of curvilinear effects based on a-priori theorizing (Edwards, 2002). This involves a hierarchical analysis of polynomial equations (Venkatesh & Goyal, 2010). Our hypothetical model can be described by the following equation:

[10] Since there were different indirect paths between SQ and the risk dimension, the indirect effect could not be definitely specified. We thus used the term "Med" as surrogate for the possible Mediator.

$$Z_{PI} = a_0 + b_1 X_{PsyR} + b_2 Y_{SQ} + b_3 (X_{PsyR} * Y_{SQ}) + b_4 Y_{SQ}^2 + b_5 (X_{PsyR} * Y_{SQ}^2) + b_i + \varepsilon_0$$

Equation 2

In this article we concentrated our examination on the effect of psychological risk as the central outcome risk, but also repeated all tests with the other risk variables. To calculate the polynomial regression we created single-item vectors by averaging and standardizing the items of each construct. Furthermore, we scale-centered each variable by deducting the midpoint from each value (resulting in a -3 to +3 centered-scale, corresponding to the 1 to 7 scale). This prevents issues of multicollinearity and facilitates the interpretation of the response surface. Referring to Cohen, Cohen, West, and Aiken (2013) we entered the terms from equation 2 in the following order: Block 1 – Control variables; Block 2 – Linear effects induced by central independent variables; Block 3 – Interaction terms of risk and SQ; Block 4 – quadratic effect of SQ; Block 5 – cubic effect determined by the psychological risk multiplied with the quadratic SQ effect[11]. Referring to Edwards (2002) we first tested our constrained model (the linear effects) against the unconstrained higher order models. In line with findings by Gefen and Pavlou (2012) the highest explained variance resulted for the unconstrained third-order model, with a significant difference to the linear (R^2 = .46) and the quadratic effect (R^2= .46). The cubic model was thus the best-fitting one for our calculations. As illustrated in Table 4.2, we found support that SQ quadratically moderates the direct effect of risk on purchase intention (β = .07, p < .01). This is in line with H10 and produces a lower effect compared to the one that was found by Gefen and Pavlou (2012) for the quadratic moderation of PEIS (β = .13, p < .01).

In the final regression step, an extra 34.3% of variance beyond the control variables could be explained by the additional factors (~12.7% vs. 47.0%). The linear effect accounted for 33.4% of the variance. Neither the interaction term nor the quadratic effect of SQ further explained a significant increment of variance (0.1% and 0.0%). Finally, the cubic effect explained an incremental 0.9% of variance, which constitutes a significant increase of explained variance. To specify this increase, the effect size of the higher order term compared

[11] It is noteworthy, that all higher order terms should be included in a regression until no significant increment of variance in the DV is explained (Edwards, 2002). We thus included the quadratic effect of X_{PsyR}^2 and the cubic effects of X_{PsyR}^3, $X_{PsyR}^2 * Y_{SQ}$, Y_{SQ}^3 in an exploratory fashion, though there was no indication of substantial effects in the literature. As assumed the neglected terms had no significant influence on the purchase intention. In a second exploratory analysis we additionally involve the 4.order effects in the regression. However, this revealed no significant variance contribution.

to the linear effect was calculated by analyzing Cohens`s f² value derived by the ΔR². This revealed a medium to large-sized effect ($\Delta R^2 = .09$; $f^2 = .0170$)[12].

Table 4.2 *Hierarchical Polynomial Regression Results for Purchase Intention.*

	Step 1	Step 2	Step 3	Step 4	Step 5
	Control Effects	Linear Effect	Interaction Effect	Quadratic Effect	Cubic Effect
Step 1: Control effects					
Gender	.015	.008	.009	.008	.006
Age	.011	.033	.029	.030	.023
Education	-.104**	-.062*	-.065*	-.066*	-.075**
Income	-.017	-.023	-.023	-.023	-.017
Smartphone Ownership	-.105**	-.066*	-.066*	-.066*	-.071*
Travel Insurance Ownership	.043	.033	.032	.032	.030
Interested in Travel Insurance	-.177**	-.102**	-.098**	-.099**	-.093**
Intention to Buy Travel Insurance	-.040	-.033	-.030	-.031	-.035
Used Device for Study Participation	-.086*	-.073**	-.072**	-.072**	-.074**
Mobile Device Expertise	.197**	.111**	.108**	.108**	.100**
Insurance Expertise	.040	.051	.052	.052	.042
Step 2: Linear effects					
Risk		**-.407****	**-.408****	**-.408****	**-.496****
SQ		**.334****	**.337****	**.334****	**.348****
Step 3: Interaction effect					
Risk x SQ			-.033	-.034	.002
Step 4: Quadratic effect					
$(SQ)^2$				-.006	-.012
Step 5: Cubic effect					
Risk x $(SQ)^2$					**.069****
Adjusted R^2	.127	.461	.462	.461	.470
$\Delta F(\Delta df)$	11.1(11)**	233.3(2)**	1.8(1)	0.1(1)	14.2(1)**

Notes. ** $p < .01$; * $p < .05$. The numbers in bold highlight significant linear, quadratic and cubic effects.

Referring to Edwards (2002) support for the model rests on four conditions: (1) The variance explained by the unconstrained model is different from zero; (2) the coefficients show the predicted pattern (significant and in the predicted direction); (3) constraints imposed by the

[12] According to Aguinis et al.'s (2005) 30-year review of effect sizes for moderations, the average effect size for applied psychology and management studies amounts .009, what is less than half of the fix cut-off value for a small effect recommended by Cohen (1988). Taking Cohen's cut-offs thus bears the risk of overseeing prevalent moderation effects. It is therefore suggested to compare the effect sizes with findings from the same field of research (Aguinis et al., 2005). In consequence, our interpretation is based on the realistic values of .005 for a small effect, .01 for a medium sized effect and .025 for a large effect size as suggested by Kenny (2015).

hypothesized model are satisfied[13]; and (4) there is no significant increase in the variance explained by higher-order terms beyond the hypothesized ones. In support of the investigated model these criteria were fulfilled. As illustrated in Appendix 8.6, the quadratic moderation of SQ can also be confirmed for performance risk, time risk and financial risk. For privacy risk, only a linear association to purchase intention was supported. Additionally, IQ also revealed a quadratic moderation for psychological, performance and financial risk with purchase intention. For time risk and privacy risk, we only found significant linear effects. To specify the quadratic moderation of SQ with psychological risk, we finally plotted the unconstrained cubic model by using the response surface method (Edwards & Parry, 1993).

4.6.4 Response Surface Methodology.

The RSM recently gained momentum in explaining complex patterns of relationships between variables (Brown et al., 2012; Gefen & Pavlou, 2012; Venkatesh & Goyal, 2010) and enables a precise description of three-dimensional surfaces that arise from polynomial regression equations (Edwards & Parry, 1993). The RSM supports a precise interpretation and analyzation of higher order equations (Box & Draper, 1987; Myers, 1976) and gives further illustrative insights beyond polynomial regressions (Gefen & Pavlou, 2012). In our case, the RSM is thus suitable for giving a specific view on the quadratic moderation of risk through SQ. For the interpretation of the response surface Edwards (2002) proposes three key features: (1) The stationary point of the surface, meaning the point at which the slope of the surface is zero in all directions. This inflection can be a maximum, minimum or saddle point. (2) The principal axes of the surface, which intersect at the stationary point and run perpendicular to each other and (3) the slopes along lines of interest, which are mainly captured by the X = -Y line and the X = Y line. However, these lines were of minor interest in the present study compared to the slopes of psychological risk along different magnitudes of SQ, in particular Y = -3, Y = 0 and Y = 3. We also examined the curvature at X = -3 and X = 3 to pinpoint the course and threshold of purchase intention that result from the quadratic moderation. Since service-based m-commerce is in an early stage, we assume that purchases will only take place under conditions of high certainty. Thus, we stipulated a value of one as a threshold, above which purchases become likely instead of zero (cf. Gefen & Pavlou, 2012). This is displayed by the dashed line in the responses surface shown in Figure 4.3. The

[13] Since our hypothesized model did not include an algebraic difference (Bolton & Drew, 1991) in the equation, the only constraint that had to be tested is constituted by the higher-order cubic terms (Venkatesh & Goyal, 2010).

RSM was applied by using the unstandardized regression weights inserted in the initial Equation 2:

$$Z_{PI} = 1.607 - 0.528 * X_{PsyR} + 0.481 * Y_{SQ} - 0.031536 * X_{PsyR} * Y_{SQ} - 0.013 * Y_{SQ}^2 + 0.039 * X_{PsyR} * Y_{SQ}^2 \qquad \text{Equation 3}$$

To ensure the reliability of the significance of the slopes Edwards and Parry (1993) recommended purifying the data by applying either the bootstrap or jackknifing methodology. We thus implemented 10,000 bootstraps in the regression analysis in order to create proper confidence intervals for the coefficients.

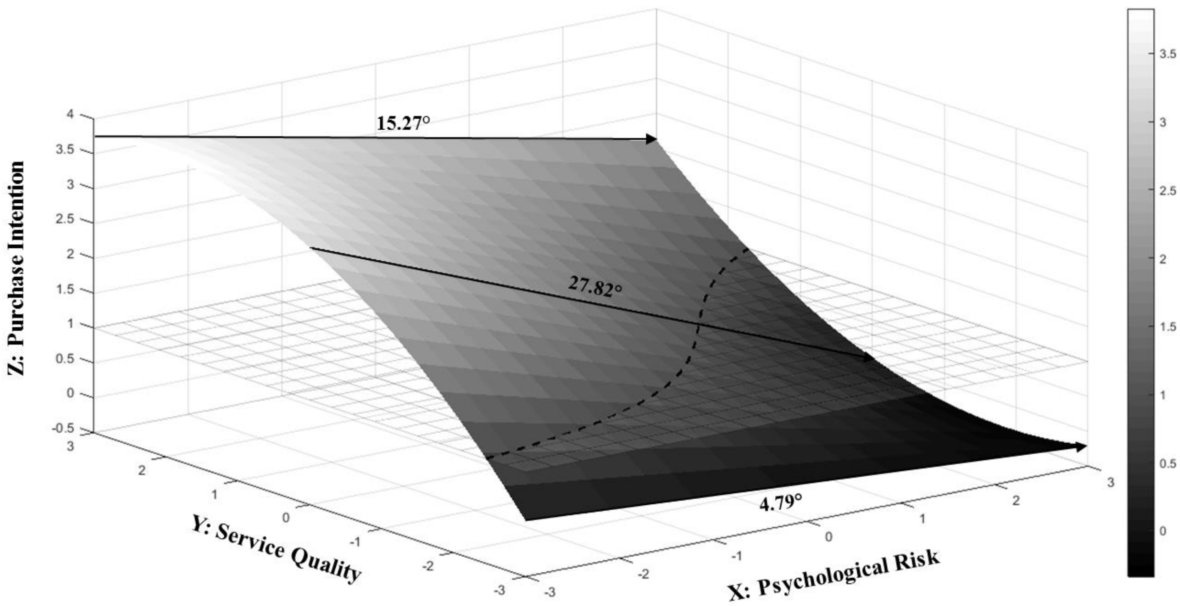

Figure 4.3 Response surface for the quadratic moderation. The graph shows the effect of risk on purchase intention through service quality. Black arrows depict the effect of risk at different levels of service quality in degree. The dashed line mirrors the potential threshold above which purchases take place.

Regarding our hypothesis we first found two stationary points, one at X_1 = -1.29, Y_1 = 4.12 and a second at X_2 = 1.97, Y_2 = -3.30. Both points fall out of the shown graph. However, given the graphical interface it can be presumed that point one marks a local maximum and point two marks a local minimum. This implies that purchase intention is maximized at the SQ value of 4.12 for a given moderate to low levels of risk. Nonetheless, as pointed out by Brown et al. (2012) there are no definite values regarding the stationary points and principal axes for third-order polynomial equations. We therefore relied more strongly on the slopes along lines of interest at different levels of SQ. As key anchors of those levels we used a middle category of Y = 0, two extreme categories of Y = -3 and Y = 3, and, as recommended by Cohen and Cohen (1983), the values one standard deviation below and above the mean (M_{SQ} = 0.44) of the respective variable. Firstly, we found a significant slope of 27.82° at Y = 0 (t = -13.19, p < .01), and of 15.27° at Y = 3 (t = -3.26, p < .01), but a non-significant slope of 4.79° at Y = -3 (t = -0.85, p = .40). We further found two significant slopes for the value of SQ one SD above (t = -11.22, p < .01) and below (t = -10.94, p < .01) the mean of SQ. The maximized risk influence appears at a SQ value of 0.41 (28.10°) which nearly corresponds with the mean of SQ of 0.44. Finally, we investigated the transition points of significance for the slopes along the Y-axes, which constitute the boundaries of risk influence with respect to SQ. These borders were at Y = 3.33 and -2.69, meaning that risk has no significant influence on purchase intention beyond these values. Additionally, we analyzed the local extrema regarding purchase intention, to gain knowledge about the optimum of SQ at high, moderate and low levels of risk. As depicted in Figure 4.4, for the high risk level (X = 3) we found a local maximum of purchase intention at Y_{SQ} = 2.22 and for moderate risk levels (X = 0) at Y_{SQ} = 18.49. For low risk levels (X = -3), we found a local minimum of purchase intention at Y_{SQ} = -1.87.

Also, we tested the curvature along the high and low risk level. This was accomplished by building the second derivation of Equation 2 to y and inserting the respective values of x. For the low level of risk we found a negative value for $f''_{-3}(y)$, which implies a concave downwards curvature, and a positive value for $f''_{3}(y)$, which implies a convex upward curvature at high levels of risk (see Figure 4.4). While both quadratic effects are leveled by the presence of the opposite curvature, a sample split (with X_{Risk} < or > 0) into a high and low risk sample leads to two significant quadratic effects of SQ with opposite direction ($\beta_{high\ risk}$ = .062, p < .05; $\beta_{low\ risk}$ = -.10, p < .01). Overall, these results provide substantial support for H10.

4.6.5 Group Differences in SQ and the Impact of Risk.

To obtain additional evidence in a practical relevant design, we finally investigated H10 in a 2-by-1 between-group analysis. Therefore, we divided the sample into a higher SQ (HSQ; M_{HSQ} = 0.54) and lower SQ (LSQ; M_{LSQ} = 0.31) condition, induced by different numbers of service features in each treatment. As mentioned above, the manipulation check confirmed the effectiveness of the treatments. Following H10, an increasing amount of SQ should alter the influence of risk on purchase intention. In line with this assumption, the data revealed a significant interaction effect of small size ($\beta_{SQ\text{-}condition*PsyR}$ = .06, p < .05, f^2 = .0062), constituting a reduced influence of psychological risk with increasing SQ (β_{LSQ} = *-.55,* β_{HSQ} = *-.44)*.

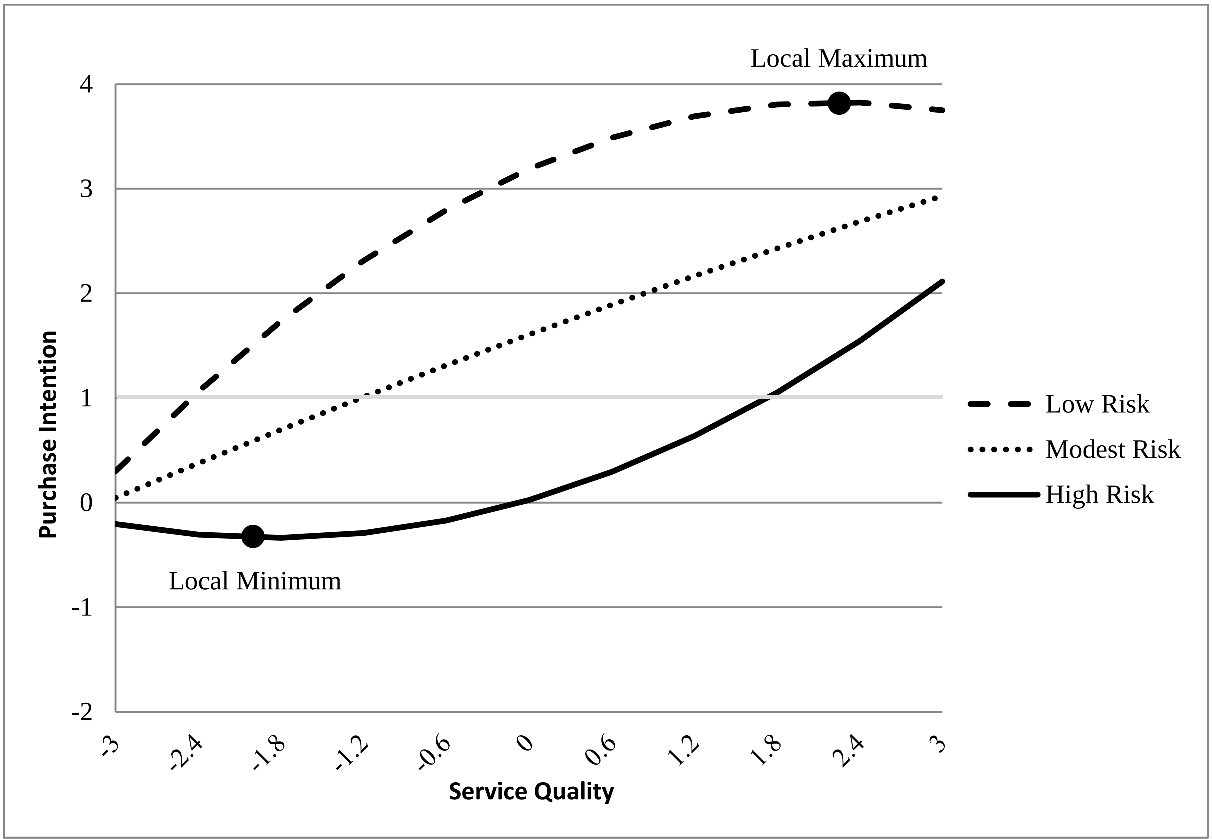

Figure 4.4 Curvatures of the effect of service quality in dependence of the risk level.

4.7 Discussion

In this article we aimed to evaluate the potential of service quality to regulate the emergence of risk in m-commerce. Therefore, we built upon and extended the understanding of the concept of perceived risk in m-commerce by providing a comprehensive analytical approach towards its effect on purchase intention. To approach this, we applied four methods that specify the effect of risk under the influence of SQ from different angles: structural equation modeling, polynomial equation modeling, response surface methodology and a between-group design. Based on the SEM, we obtained support for a hierarchical emergence of risk deriving from concrete risk cues up to abstract risk estimations. It was shown that performance risk is fueled by privacy risk, and predicted financial, time and psychological risk. Although we found marginal significant effects for the influence of financial and time risk on psychological risk, performance risk appeared to explain the outweighing amount of variance. Finally, the relation of all risks with purchase intention draws upon a mediation through psychological risk. Our investigations regarding SQ and IQ revealed a strong positive impact of both on each risk dimension as well as on purchase intention. The relevance of SQ is further confirmed as it induces higher perceptions of IQ in mobile online marketplaces.

The polynomial equation modeling concretized those effects by confirming a quadratic moderation of the effect of risk on purchase intention through SQ. This means that low SQ causes an irrelevancy of risk for consumers, since a purchase lacks in attraction due to high personal vulnerability. Under the condition of enhanced SQ, risk increasingly enters the decision process of consumers and gains in relevance. The maximum impact of risk was found close to the mean of SQ (at 0.406). Beyond this value, the impact of risk is continuously mitigated by rendering sufficient assurance for a self-determined successful purchase. The response surface method delineated a continuous growth of purchase intention with increasing SQ, for modest and high levels of risk.

In the last step, a between-group comparison showed that the enrichment of m-commerce with service features alters the influence of risk by increasing the perception of SQ. In a conclusive polynomial regression the quadratic moderation was replicated for SQ with performance, financial and time risk and for IQ with performance, financial and psychological risk. Privacy risk in general and time risk with IQ as moderator revealed only a linear effect on purchase intention.

4.7.1 Theoretical Implications.

The present article contributes to the recent literature by extending knowledge in four directions: Firstly, it provides detailed insight into the structure and dimensionality of risk. Secondly, it extends existing knowledge about the boundaries of risk for complex products. Thirdly, it reconsiders the role of SQ as a potential antecedent to IQ in modern sales channels. Finally, it proposes a comprehensive methodological procedure to elaborate on complex interrelationships in IS research.

The literature about the interactions of risk has produced a manifold understanding of risk dimensionality in technology adoption, but still lacked a common consideration and clarification of the interdependencies between these dimensions. Therefore, our investigation first encountered the constructional disunity (Lim, 2003) and the continuous demand for a more detailed investigation of the risk dimensions (Featherman & Hajli, 2015). Consistent with Cunningham (1967) and Keh and Pang (2010), the data showed that performance risk acts as a central source for other risks, especially psychological risk. In line with Stone and Grønhaug (1993), it was further shown that every risk directly or indirectly translates into a psyche status of discomfort. The structure adds depth to the concatenation of financial and time risk, according to assumptions by Kim et al. (2008) who saw time risk as part of financial risk. Finally, the highest model fit was constituted by an indirect effect of all risk dimensions on purchase intention, supporting a mediation through psychological risk. The stated structure transfers the concept of non-personal risk that are evolving to personal risks on to the common dimensional structure of risk in IS research. The results challenge findings based on equivalent risk dimensions in affecting behavioral intention, as described, for instance, by Lee (2009), Featherman and Pavlou (2003), Martins et al. (2014), Crespo et al. (2009) or Yang et al. (2015). It is shown that mediating effects mitigate and cover the impact that a single risk can have on behavioral intention.

Secondly, the findings extend the understanding about the ubiquitous effect of risk in online transactions. The perception of risk is constrained by boundaries that are influenced by the SQ in a quadratic fashion (inverted-U). Therefore, our investigation supports the generalizability of prior findings regarding a curvilinear association of risk and purchase intention triggered by variables that enhance the perceived structural effectiveness of an institution (Gefen & Pavlou, 2012; Pavlou & Gefen, 2004) as can be assumed for SQ and IQ. The results allow a transfer of the moderation effect validity from e- to m-commerce, from goods to complex products, from well-known to unknown sales environments, from the post- to the pre-adoption phase of a technology and from PEIS to SQ, IQ and different risks. Nonetheless, in contrast to Gefen and Pavlou`s (2012) findings, our data support a persistent effect of risk up to the maximum of SQ. While Gefen and Pavlou (2012) report high transaction intentions only for moderate values of PEIS, our findings instead followed "the more, the better" principle regarding SQ. As argued by Özpolat et al. (2013) this can be explained by more uncertainty through a lower seller prominence and experience (novice shoppers) in the tested mobile channel in combination with the higher product complexity for insurance. In fact, although Gefen and Pavlou (2012) found a small direct effect ($\beta = -.12$) for risk on purchase intention for the platforms Amazon and eBay, we found a considerably higher direct effect ($\beta = -.50$) for the unbranded mobile app. The addition of risk and SQ explained a further increment of 33.4% of variance compared to 2.7% for Gefen and Pavlou (2012). The results therefore give a concrete estimate about the development of the quadratic moderation with increasing levels of uncertainty. This also sheds light on the findings of

Özpolat et al. (2013) who found that two or more trust seals hamper the likelihood of purchase completion in e-commerce. Nonetheless, they pointed out that the completion rate for smaller retailers and new shoppers takes a higher benefit by trust seals. Interpreted with our findings, too many seals push the SQ over the peak of purchase intention ("feature fatigue") and lead to a reduced completion rate particularly in common situations. Small retailers and new shoppers inhere higher levels of uncertainty, which in turn shifts the need for service such that even high rates of SQ improve purchase intention. This also explains that assurance seals are more appreciated in the last decision steps prior to a purchase, when the risk perception is maximized (Özpolat et al., 2013). The upper boundary of risk accordingly disappears under high uncertainty. In conclusion, we stress that although risk has boundaries, these vary in dependence of external factors such as the complexity of the product, the innovativeness of the product or channel, experience or demographics. This challenges findings regarding the effect size of risk has on purchase intention under the aspect of moderating effects (Grewal et al., 2007; Gupta & Kim, 2010; Luo et al., 2010; Nicolaou et al., 2013; Wu & Wang, 2005).

Thirdly, this article gained valuable insights into the effectiveness of service and IQ in order to reduce risks. The results correspond with given findings, assuming that high service and IQ leads to an increased process convenience, control, understanding, skillfulness, trust and efficiency (Pavlou, 2003; Ranganathan & Ganapathy, 2002; Zhou & Lu, 2011). Additionally, SQ revealed a positive impact on IQ. This confirms the understanding of IQ as a mediator between SQ and behavioral intention in online channels as stated by Pearson et al. (2012) and clarifies the discordance about the role of IQ (Alba et al., 1997; Delone & McLean, 2003; Ding et al., 2011; Montoya-Weiss et al., 2003; Swaminathan et al., 1999). While SQ and IQ might be equivalent constructs in offline channels, our findings support that mobile online decisions are dominated by superficial, early external cues that allow the consumer to draw inferences considering the quality in other areas of the provider. Overall, the results stress the importance of SQ in order to increase purchase intention and strengthen recent theorizing about the way it exerts influence. Moreover, the study offers a tangible approach for the inducement of SQ realized by the implementation of service cues. This enhances knowledge about the positive concatenation of service cues and purchase intention as also found by Richard (2005) for navigational cues.

Fourthly, the study establishes a methodological approach to comprehensively explore sophisticated variable relationships. The four applied methods reinforce the need for a multi-method approach to allow for strength and weaknesses that are inherent to each single method. More precisely, the structural equation model allows the examination of multivariate regressions all at once. Although SEMs offer the possibility to test several models (e.g. higher-order models) against each other by the manual addition of further terms and comparing the goodness of fit, it lacks an automated procedure to add further predictors in a stepwise manner. By comparison, the polynomial equation modeling offers a convenient procedure to assess the incremental gain of each step, but does not specify the relations among the independent variables. Apart from this, it seems mandatory to test the higher-order effects in order to meet reliable interpretations. This article therefore supports the integration of multivariate modeling and polynomial modeling in one approach to enhance the statistical fundament of IS research. In addition to this, it was shown that a response surface provides a thorough understanding of the shape of the effect. This enables concrete statements for the boundaries, curvatures, maxima and minima of a variable's impact and thus extends the implications for theory and practice. Finally, the rendered effects are generalizable and can be recovered in practice. We addressed this issue, by implementing a between-group design. As predicted, it was shown that the influence of risk alters, along with different amounts of SQ, and thus strengthens the support for a meaningful outcome.

4.7.2 Practical Implications.

The study proposes three major practical implications for m-commerce: Firstly, the outcome highlights predestined fields of action according to the most dominant dimensions of risk. Practitioners should therefore primarily invest in the privacy and performance risk of their product, prior to financial and time risk. Assurance seals and certificates have hereto found to be a good means of increasing trust and likelihood of a purchase, albeit moderating effects have to be accounted for (Özpolat et al., 2013; Özpolat & Jank, 2015). Performance risk can, on the one hand, be addressed by following high ethical and moral standards; for example, by refraining from withholding or providing misleading information. On the other hand, a good performance should be further supported by key indicators such as online reviews, guarantees or summaries of product aspects.

Secondly, the results encourage the enhancement of SQ in mobile sales applications, since it mitigates risks and increases IQ and purchasing intention in a direct way. The response surface displayed increasing purchase intention when SQ surges, independent of the perceived risk level. Nevertheless, there are differences in the trend for low levels and high levels of risk. For practitioners this suggests that purchases under low risk need to be provided with "high to very high" service quality (Y_{SQ} = 2.22) to maximize buying intention for complex products. A further extension reduces purchase intention at this level. For purchases under high risk, small amounts of SQ (up to a value of Y_{SQ} = -1.87) harm the willingness to buy (i.e. by raising confusion). This means that practitioners at least need to exceed this threshold to recognize a positive effect on purchase intention. For moderate levels of risk, an increase of SQ generally causes an increase of purchase intention (at least up to the theoretical level of Y_{SQ} = 18.49). Therefore, for products with high complexity, a maximization of SQ is recommendable at the current state of m-commerce. However, since the value of risk can decrease with higher experience over time (as apparent for Amazon and eBay), the value of SQ needs to be monitored and adjusted, along with the product-channel-cycle or the individual development. This encourages the development of a personalized service environment in consistence with consumers' needs.

Moreover, the risk influence is maximized for modest SQ-level (Y_{SQ} = 0.41). This suggests that discomfort, mental stress and tension play the most influential role for people that are provided with a moderate amount of service features. The presented unmodified app (also blank version or control treatment) taken from an app store revealed exactly this moderate SQ level (M_{SQ} = 0.31), indicating that m-commerce in the insurance industry currently maximizes the risk influence on purchase intention. In this context, implementing further SQ in the form of decision aids can lower the emotional states of uncertainty and help to provide people with sufficient confidence to buy the product. For now, it is not feasible to completely avoid psychological risk for complex products in m-commerce according to the persistent risk effect, albeit the transition point to insignificance (X_{Risk} = 3.33) seems to be achievable in the near future. Practitioners should work towards this target by extending the service feature portfolio to establish a convenient mobile purchase in upcoming years.

Thirdly, the study confirmed the implementation of service features as an effective means to enhance the perceived SQ. As previously stated, a combination of technology mediated features as for example a helpline button, and technology generated features such as a FAQ button, test and assurance seals, information boxes referring to the product and operator guidance, can leverage the perception of SQ. Therefore, m-commerce designers need to include a balanced set of human-technology mediated and technological generated services. For example, Ranganathan and Ganapathy (2002), Froehle (2006), Ahn et al. (2007) or Hausman and Siekpe (2009) propose efficient sets of service tools. These include navigational tools, search engines and policy wrap-ups and overviews, online reviews, product comparisons, email and live chat, contact addresses and agent locators, different price payment options and guarantee offers, etc. However, it is noteworthy, that an overload of features can harm buyers' completion rate (Özpolat et al., 2013) and should thus be balanced with the context of usage. Our study gives concrete guidelines for the level of service which needs to be provided and can thus assist in the efficient selection of service features for m-commerce.

4.7.3 Limitations and Future Research.

There are some limitations in this research, noted in the following. The study investigated a particular case of m-commerce, namely the sale of insurance. This market is characterized by high complexity, channel newness, and consumers with low familiarity and experience. Although this allows practical insights for other service-based sectors such as mobile-banking or travel booking, it has to be questioned if other areas of m-commerce follow the same pattern. Complexity could further be confounded with the newness of m-commerce, such that the specific origin of the deviations compared to findings of Gefen and Pavlou (2012) is not clearly identifiable. Future studies should thus invest in elaborating the external factors that influence the shape of the quadratic moderation, such as differences in complexity, channel, and demography.

Furthermore, we referenced SQ to PEIS (as proposed by Pavlou and Gefen (2004)) as similar constructs since they are composed by similar cues, such as payment guarantees. Differences could nevertheless arise from the deviating notion of the variables and constrain the comparability. This also applies to the interpretation of the level of complexity and channel newness as the origin of the increased influence of risk. Here SQ could engender a different strength of influence on risk and thus alter the boundaries of risk. A future investigation should ensure the comparability of PEIS and SQ by an in-depth investigation of its relationship.

Additionally, we found a small effect size under reference to the effect sizes proposed by Aguinis et al. (2005). Two reasons can be remarked in this association: On the one hand, we conducted an online manipulation constituted by illustrations of an existing app. It may be argued that the exposition to the manipulation in this design is difficult to ensure, since participants may oversee the upgraded details. Although significant in the manipulation check, the differences between condition A and B were rather small, giving an explanation for the small effect size. Therefore, our findings constitute a conservative result regarding the altered effect of risk in the two conditions. An extensive exposition with an app in a field study could obtain a more reliable picture of the risk effect in different service conditions and should be targeted in the future. The manipulation was further composed by a selection of six service elements, derived from the e-commerce literature. These elements may only produce limited effects regarding SQ in m-commerce due to a small perceived usefulness. To draw detailed conclusions about the effectiveness of different service features a building-up study should be dedicated to a broader set of features and focus on its individual effectiveness. For the background of m-commerce, this could involve a differentiation into technology-mediated and technology-generated service or graphical and text-based service features.

4.8 Conclusion

The present article draws a comprehensive picture of the influence of risk on purchase intention in the uprising market of mobile commerce. It extends the understanding of the dimensionality of risk by defining a hierarchical process of risk emergence and by identifying service quality as means to encounter these risks. For complex products, our results propose that the enrichment of mobile commerce with service features improves the purchase intention at almost every stage of risk except for very low levels. Therefore, the outlined results give instructions on how to tailor service suitable to the amount of risk and enable flexible consumer support in line with the product lifecycle. Service should accordingly be downsized depending on the maturity of products and channels. In summary, these results provide a further step for handling risks in the digital marketplace and to enhance the success of mobile commerce.

STUDY 4

5 Ruling out the Service Deficit in M-Commerce: How Service-Task-Technology Fit can Support the Sales of Complex Products

5.1 Abstract

Mobile commerce still experiences high drop-out rates throughout the sales process. This is especially common for complex products, such as insurance, where consumers often explore products online initially but complete the purchase offline, where they have direct human assistance which can help them to better understand the product and reduce associated risks. To facilitate the adoption and execution of complex product transactions online, we applied task-technology-fit considerations to service that is provided on digital devices. In particular, we propose a comprehensive technological service (CTS), meaning the combination of technology-mediated service (TMS) and technology-generated service (TGS) as central elements of face-to-screen (FtoS) service. Based on an experimental approach we find a significant superiority for the synthesis of TMS and TGS in terms of service quality and information quality, as well as concerning consumers perceived financial risk, psychological risk, ease of use and purchase intention. In contrast, over-reliance on either TMS or TGS reduces perceived service and information quality and reinforces the perception of several risks. Our findings extend the theoretical knowledge on the mechanisms that are inherent to FtoS service and give concrete practical implications for the future design of services in m-commerce.

5.2 Introduction

Many companies use m-commerce to provide their consumers with easy time- and location-independent access to their products and services. It helps companies to shift their usually expensive local service operations to the digital world. However, m-commerce adoption for complex products lags behind. Mobile insurance sales, for example, remain among the least attractive categories in m-commerce (Statista, 2013). A key reason for this reluctance is product-inherent complexity, when a product’s characteristics and contractual details require significant effort to be fully understood, in order to minimize associated risks (Cacioppo, Petty, Feinstein, & Jarvis, 1996). A comprehensive service that can help to mitigate these risks is therefore indispensable. It seems that m-commerce still lacks sufficient integration of traditional offline and modern online service elements as demonstrated by other mobile providers such as Amazon and Ebay (Gefen & Pavlou, 2012). This has led to a “research online, purchase offline” (ROPO) principle for insurance consumers, implying an online-based product research followed by a traditional offline purchase (Jin, 2012). It follows the consumers’ inclination to strive for self-determination and control in the purchase process (Collier & Sherrell, 2010). The observed ROPO split ultimately strengthens the perception of insufficient service to support mobile sales and suggests that new approaches are required to satisfy consumers’ needs for service in m-commerce.

Potential means to facilitate m-commerce adoption for complex products are technology-mediated service (TMS) and technology-generated service (TGS) as introduced by Froehle and Roth (Froehle & Roth, 2004). Both TMS and TGS are subtypes of the so-called face-to-screen service (FtoS). TMS represents a form of personnel communication that is exclusively conducted via a technology-based medium, for instance telephone, e-mail or chat. TMS specifically involves human service, in contrast to TGS which is a fully automated service (Froehle, 2006). Both types are generally captured as face-to-screen services (FtoS).

Contemporary corporate approaches towards selling complex products via m-commerce rely primarily on TMS (Heinze & Thomann, 2015). This contradicts the recently established ROPO attitude of consumers as it lacks sufficient sources to research and neglects the need for self-controlled purchases due to missing self-service options. Sole reliance on TMS fails to address shortcomings in human-based service, such as unethical behavior, poor employee skills or temporal and spatial boundedness (Giebelhausen, Robinson, Sirianni, & Brady, 2014; Keh & Pang, 2010; McClaren, 2013; Meuter et al., 2000). By contrast, sophisticated TGS has already been established in online retail with simple goods; for example one-click ordering, trust-e symbols or integrated search engines and provides a range of advantages for consumers (Parasuraman et al., 2005). Nevertheless, scholars pose concerns about the efficiency of TGS and TMS used separately (Simon & Usunier, 2007). In response, Selnes and Hansen (2001) propose a hybrid model that integrates self-service with personnel service, implying a migration of TMS and TGS in our context. However, whether TMS or TGS used individually are capable to facilitate m-commerce adoption for complex products remains empirically unexplored, as does whether the combination of both (which we refer to as comprehensive technological service (CTS) outperforms each of the two through synergies. We reduce the existing research gap on the configuration of service in digital channels and pose the following research question: *How do TMS, TGS and its combination affect the adoption of m-commerce for complex products?*

To answer our research question we draw on established theories from the information systems (IS) literature. At first, it is assumed that the demand for service depends on the task that has to be completed. As the basis of our theorizing we thus refer to the task-technology-fit (TTF) theory. This defines the degree to which a technology supports the individual in performing a task (Goodhue & Thompson, 1995). To quantify the impact of different service manifestations, we base our evaluations on the constructs of both service quality and information quality. These constructs constitute the basis of the information systems success model (ISSM) (Delone & McLean, 2003) next to engineering oriented characteristics (~[14] system quality) as the three main indicators of web quality. To disentangle the service interaction, our interest is focused on the non-engineering characteristics. To further estimate the hypothesized effects, we also use the extended perceived risk-technology acceptance model by Pavlou (2003). This captures different risk facets together with perceived usefulness and ease of use, and has proven its relevance regarding the acceptance of complex products.

Our results extend the recent literature by obtaining new insights into the role of human and technological web assistance in m-commerce. This leads to four major contributions for research: (1) We refine the contemporary task-technology fit literature by incorporating the concept of service as a further relevant variable of fit in order to reach acceptance. (2) We clarify the impact of human service in the form of TMS on purchase intention in m-commerce in contrast to TGS. This allows for a better understanding of specific advantages and disadvantages of each service approach. (3) We elaborate the knowledge about psychological mechanisms which determine the acceptance of complex products in m-commerce, especially regarding the association of service with perceived risks. (4) Finally, we provide insights into the service perception in the first moments of a consumer interaction with m-commerce prior to the personnel provider contact. For practice, this leads to a better understanding of consumer interactions in m-commerce and it reveals valuable implications for the design of mobile apps for complex products.

The remainder of this article reads as follows: First, we give an overview of the theoretical background and derive our research hypotheses. Subsequently, we present our

[14] In this article we use the sign „~“ as abbreviation for „corresponds to“

research methodology and report of results. Finally, we discuss theoretical and managerial implications and depict opportunities for future research.

5.3 Theoretical Background

5.3.1 Types of Face-to-Screen Service.

There is a long tradition of research on business to consumer interactions assuming the physical presence of the consumer while consuming the service. Face-to-face service has thus been well investigated in the past. Nevertheless, virtual interaction has taken the world by storm and requires an updating of research to understand its effects on consumers' satisfaction (Froehle, 2006). Mobile service by definition is provided via screen and contains either personnel web assistance (~TMS), plain technological web assistance (~TGS), or a combination of both (Froehle, 2006). The latter is referred to as comprehensive technological service (CTS) in the following. TMS mainly comprises a human-based service via phone, chat, email or voicemail. It is determined by knowledge, skills, and abilities as well as by the individual traits of its human entity (Froehle, 2006). These properties strongly affect the effectiveness of the support and the perceived quality of service. On the one hand, TMS enables a quick, reliable and competent processing of queries and has, in addition to consumers' loyalty and satisfaction, a positive impact on feelings of perceived control and commitment towards a relationship (Ding et al., 2007; Gremler & Gwinner, 2008). Service employees can also easily understand consumer requests, provide them with advice and communicate in an adequate manner in order to demonstrate empathy (O'Brien, Shank, Myers, & Rayner, 1988; Simon & Usunier, 2007). This finally leads to a flexible and personalized interaction, and assists consumers in making a decision. Many providers have thus identified the potential of TMS (Gremler & Gwinner, 2008). On the other hand, disadvantages arise from high labor costs, less possibilities to standardize the consumer contact, inaccurate appraisals and solving of requests, long waiting times and an opaque information provision (Dabholkar, 1996). This can lead to frustration, uncertainty and mistrust and is even intensified for TMS through missing contextual information from in-store encounters (Chircu & Mahajan, 2006).

In contrast, the reliance on purely electronic service known as TGS has become increasingly common, accelerated by the implementation of digital service features such as frequently asked questions (FAQs), search functions and information buttons (Curran, Meuter, & Surprenant, 2003). These features place a strong emphasis on consumer self-service and reduce the need for personnel counselling (Curran & Meuter, 2005). For example, Amazon can be seen as one best practice in applying such self-service technologies (SST). The latter is defined as technology that is performed without any interaction or association with employees of the service provider (Curran & Meuter, 2005; Meuter et al., 2000). From a corporate perspective, this provides several benefits such as the standardization of service delivery, expanded options for delivery, reduced labor costs (Curran & Meuter, 2005; Curran et al., 2003; Dabholkar, 1996), differentiation through digital interaction (Meuter & Bitner, 1998) and the generation of a common understanding. However, concerns arise from technological failures, process failures, poor design and consumer-driven failure (e.g. forgotten password) (Curran et al., 2003; Meuter, Ostrom, Bitner, & Roundtree, 2003; Meuter et al., 2000), which can be fatal due to low switching costs through minimized personnel bonds (Meuter & Bitner, 1998; Selnes & Hansen, 2001). On the consumer's side, TGS increases the ability and self-confidence of consumers by providing instant information during a product encounter leading to an autonomous learning behavior. This results in higher efficiency, flexibility and delight (Bitner, Brown, & Meuter, 2000; Curran et al., 2003). Consumers obtain more control over their product selection processes; for example, by customizing the product, which enhances convenience and enjoyment while using the technology (Dabholkar, 1996). Nonetheless, there are also concerns, such as the lack of employees' individual advice, including implicit and pragmatic messages to draw proper inferences (Simon & Usunier, 2007). Additionally, consumers are confronted with an increased amount of time and cognitive effort to understand the technology as well as the product, with scant opportunity to address complex issues (Meuter & Bitner, 1998; Simon & Usunier, 2007).

5.3.2 Service and Task-Technology Fit.

In recent IS literature, the success of an IS is construed as the product of three components: service quality, information quality and system quality (Delone & McLean, 2003). M-service is hereby defined as the extent to which a mobile website or app facilitates efficient and effective shopping, purchasing, and delivery of products and services (Zeithaml et al., 2002). Zeithaml et al. (1990) proposed five relevant dimensions for the assessment of service quality: reliability, responsiveness, empathy, assurance, and tangibles. Further subcategories were later added (Barnes & Vidgen, 2001) as can be seen in Table 5.1, together with a summary of all applied constructs.

Information quality is defined as users' perceived value of all content-related information that is retrieved during an m-service encounter. This includes the accuracy, timeliness, completeness, information reliability, relevance, up-to-dateness, ease of understanding, personalization and format adequacy of all content in the m-commerce environment (Ahn et al., 2007; Delone & Mclean, 2004; Palmer, 2002; Ranganathan & Ganapathy, 2002). Both quality constructs revealed a good fit for e-commerce sites (Ahn et al., 2007), and appear adequate for m-commerce. We base our theoretical frame on the aforementioned dimensions as shown in Table 5.1.

Consumers' assessment of service results from the comparison of expected and provided service (Parasuraman et al., 1985; Pitt et al., 1995). This is in line with the task-technology fit (TTF) literature, which argues that the characteristics of technology and task should be in balance in order to meet consumers' needs (Goodhue & Thompson, 1995). More specifically, certain decision-making tasks are suited to specific levels of media richness, meaning the richness of information that is communicated through a channel (McGrath & Hollingshead, 1994). The demand for media richness increases for more complex tasks (e.g. insurance purchases) and thus influences consumers' channel choice. It is claimed that personal communication (cf. TMS) reveals highest media richness in contrast to computer systems (cf. TGS) (Maity & Dass, 2014). An integration of both, personal and computer service in m-commerce may thus increase suitability. Recent literature further posited the resource matching theory as an explanation for SST adaptation. In its essence it claims that humans have limited resources (e.g. time, space, cognitive) in managing and accomplishing a task (Anand & Sternthal, 1990). Persons prefer the technology or channel that best suits their available resources, meaning the use at their own time, speed and location of choosing, with convenient cognitive effort. The offered type of service may enhance the matching of resources and thus influence the perception of service and information quality. In conclusion, the value of a product depends on the congruence between the provided service and the product attributes placed in a certain technological environment, which we refer to as service-task-technology fit (STTF).

Table 5.1 *Definitions and Dimensions of Applied Constructs.*

Construct	Definition & Dimensions	Reference
Service Quality (SQ)	The extent to which a mobile website or app facilitates efficient and effective shopping, purchasing, and delivery of products and services. Dimensions: Responsiveness (~access), Reliability (competence), assurance (~credibility, security), empathy (~communication, and understanding the individual), tangibles (~aesthetics, navigation)	(Barnes & Vidgen, 2001; Parasuraman et al., 1985; Zeithaml et al., 2002)
Information Quality (IQ)	A user's perceived value of the information content retrieved during an m-service encounter and embraces all content related issues. Dimensions: Contents, detail, completeness, accuracy, timeliness, information reliability, and format adequacy of the app content	(Ahn et al., 2007; Delone & Mclean, 2004; Palmer, 2002; Ranganathan & Ganapathy, 2002)
Perceived Risk	A user's feeling of uncertainty, discomfort and/or anxiety, internal conflict, mental stress, concern, psychological discomfort, pain due to anxiety and cognitive dissonance.	(Cox, 1967; Cunningham, 1967; Kogan & Wallach, 1964; Pavlou, 2003)
	Dimensions:	
	Performance (PerfR):The possibility that the product does not perform as desired	(Jacoby & Kaplan, 1972; Simpson & Lakner, 1993)
	Financial (FinR): The potential monetary loss associated with the initial price, maintenance costs or compensation costs	(Jacoby & Kaplan, 1972; Roselius, 1971)
	Time (TimeR: Potential loss of time associated with all product related efforts	(Roselius, 1971)
	Psychological (PsyR): The risk of mental stress related to the purchase process	(Jacoby & Kaplan, 1972; Lim, 2003)
Perceived Ease of Use (PEOU)	Refers to the degree to which a consumer believes that using a technology will be free of effort Dimensions: Easy to learn, clear and understandable, easy to become skillful, low mental effort, controllable, user friendly	(Ahn et al., 2007; Davis, 1989; Dishaw & Strong, 1999; Pavlou, 2003)
Perceived Usefulness (PU)	In m-commerce it can be defined as the degree to which a consumer believes that using a particular technology will facilitate the transaction process Dimensions: Better decisions, efficiency, saving money, productivity, task quality, easier process	(Ahn et al., 2007; Davis, 1989; Dishaw & Strong, 1999; Pavlou, 2003)
Purchase Intention (PI)	One's readiness or likelihood to engage in a specific behavior such as a purchase.	(Ahn et al., 2007; Kanungo & Jain, 2004; Pavlou, 2003)

5.3.3 Evaluation of the Service and Task-Technology Fit.

Several variables have been found to reflect the manifestations of TTF. In our context this applies especially to perceived risk, usefulness (PU) and ease of use (PEOU) (Dishaw & Strong, 1999; Larsen et al., 2009; Mathieson & Keil, 1998). Gefen and Pavlou (2012) state that a high STTF should enhance buyers' belief "that appropriate conditions are in place to facilitate transactions with sellers" (p. 941) and thereby mitigate the role of risks in the transaction process. According to Ahn et al. (2007), service and information quality further have a beneficial effect on PU and PEOU estimations. We therefore consider the perceived risk, PU and PEOU as intermediaries between service and purchase intention in our conceptual framework.

Previously, the three constructs have already been applied to various mobile contexts (Negahban & Chung, 2014; Zhang et al., 2012). A meta-analysis of Zhang et al. (2012) supported the increasing importance of perceived risk in m-commerce acceptance and found a negative association with behavioral intention. More importantly, perceived risk has proven its importance for complex products (Maity & Dass, 2014). In m-commerce, perceived risk can be defined as the uncertainty about potential negative consequences or loss in the pursuit of a desired outcome using an m-service and the value ascribed to this consequence or loss (Cox, 1967; Cunningham, 1967; Kogan & Wallach, 1964). The notion of risks is based on different dimensions. In relation to complex products in e-commerce four factors are prevailing: performance, time, financial, and psychological risk (Crespo et al., 2009; Forsythe & Shi, 2003). Pavlou (2003) integrated the risk dimensions with PEOU and PU in one spanning model to better describe the uncertain environment of e-commerce. Analogous to this, we simultaneously consider perceived risk, PU and PEOU to comprehensively evaluate the influence of the different types of service.

5.4 Research Model and Hypotheses Development

A central goal of our work is to improve the adoption of complex products in m-commerce by promoting the service and information quality. We therefore altered the type of service that is applied in an m-commerce setting. As further dependent variables, perceived risk, PU, PEOU and purchase intention are evaluated to quantify the resulting effects. The existence of associations between these variables is derived from prior findings and is not subject to our investigation. The basic conceptual model serves to illustrate the basis of this approach and is shown in Figure 5.1.

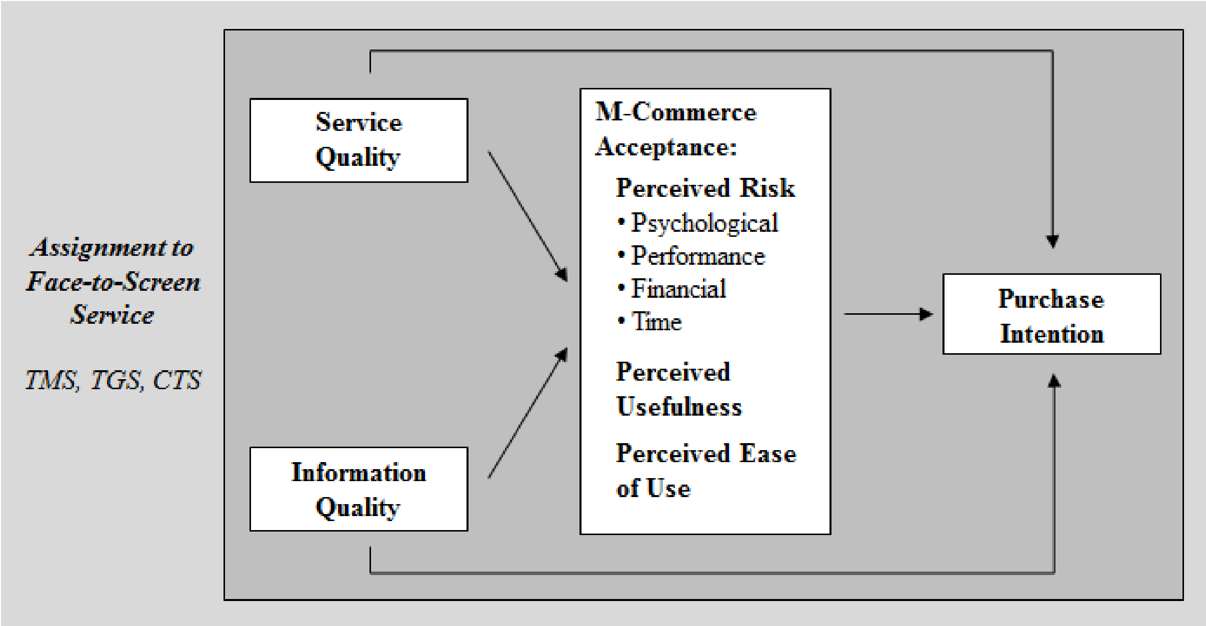

Figure 5.1 Conceptual model. TMS = Technology-Mediated Service, TGS = Technology-Generated Service, CTS = Comprehensive Technological Service.

5.4.1 Service Quality and Face-to-Screen Service.

Drawing on the STTF, a technological-based distribution channel (e.g. m-commerce) better suits to technological service approaches. For example, calling up a semi-transparent overlay with page instructions in m-commerce should be preferred to a conventional call-an-agent function due to higher suitability of the feature with m-commerce characteristics. Moreover, the "anytime, anywhere" culture provided through mobile devices (Blázquez, 2014) is opposed to the constrained accessibility and responsiveness of service staff leading to lower resource-matching perceptions for TMS. Collier and Kimes (2012, p. 40) argue: "With SST, the convenience of a transaction can conserve time and effort and allow consumers to allocate the appropriate amount of resources to effectively complete a task at their choosing."

The service quality of TMS has yet to be seen in the light of stereotypes engendered by extensive commission-driven sales in the financial sector. This means that salespeople are compensated by the amount of products they sell. As a consequence, interest conflicts, unethical behavior (e.g. withholding information) and maximization of sales by the salesperson may occur (Román & Munuera, 2005). Consumers therefore often doubt the honesty and trustworthiness of salespeople (Straughan & Lynn, 2002), feel vulnerable (Gefen & Pavlou, 2012) and have evolved stereotypes (Friedman & Srinivas, 2014). Transferred to m-commerce, the commission-driven sales process might negatively affect consumers' perception of reliability, competence, credibility and security for TMS compared to TGS.

Referring to Giebelhausen et al. (2014), higher estimations of psychological discomfort through frontline employees promote SSTs. In cases of an unpleasant service encounter, TGS can act as a respite and reduces discomfort by avoiding the exchange with the service employee. Moreover, TGS enables easier public control; for example, through independent tests and user reviews, which gives consumers higher confidence in the reliability of information.

Finally, coming from the social distance literature, TMS requires people to overcome affective and interactive barriers in initiating a contact to socially distant people. Dickson and MacLachlan (1990) argued that people shop less frequently in stores that have a great social distance to themselves. In accordance, Meuter et al. (2000) found that some people tend to use SST in order to avoid contact with sales staff. In light of the ambiguous reputation of commission-driven salespeople, and the fact that complex financial products can be assumed to be infrequently bought (Devlin, 2007; Keh & Sun, 2008), social distance might inhibit the willingness of using TMS. Social distance, however, plays no role for TGS. It is thus likely to obtain a higher appreciation in m-commerce. To summarize, TMS, rather than TGS, creates a poor fit with the task and technology. CTS therefore integrates the advantages of both alternatives which fulfills individual preferences more accurately. Finally, the following hypotheses are stated:

H1: The service quality is lowest for TMS and increases for TGS and CTS with the highest values for CTS.

5.4.2 Information Quality and Face-to-Screen Service.

With regard to information quality, both TMS and TGS have benefits and drawbacks. TMS is conducted under employee involvement and in real time, and can thus help to answer complex queries immediately, as well as to give reassurance regarding uncertainties (Selnes & Hansen, 2001). Therefore, TMS is able to transmit plenty of information under the premise of low search time and effort. However, consumers may question the reliability, accuracy, and completeness of information provided by service staff. Also the effort of obtaining information, hampered by the process of contact initiation paired with limited operating hours, may be detrimental to the service convenience (Berry, Seiders, & Grewal, 2002) and thus, negatively impact the information quality perception.

TGS otherwise reveals a better fit of information format and channel attributes, which might increase the perceived appropriateness. This involves the afore-mentioned “anytime, anywhere” accessibility of information (Collier & Kimes, 2012). Furthermore, information can be thoroughly prepared by the provider, for instance in terms of completeness, relevancy and accuracy since the information generation and consumption is separated. As mentioned earlier, content is also better controlled through public exhibition of the information in the app. On the other hand, information conveyed via TGS carries the risk of being hard to understand, irrelevant and low in quality (Gu et al., 2007). This may increase search and processing costs. TGS possesses considerable potential to obtain a high level of information quality, but obviously depends on the editorial performance.

Taken together, TGS can be assumed to reveal more tangible and suitable information for m-commerce. Nevertheless, consumers' behavior in buying complex products is evident from the usage of multiple sources of information in order to reduce uncertainty as introduced by the ROPO behavior (Jin, 2012). Providing users of m-commerce with relevant self-service information through TGS, complemented with a personnel contact for more demanding tasks through TMS, is expected to attain the highest information quality by settling the deficits of both services (Selnes & Hansen, 2001). We pose the following hypothesis:

H2: The information quality is lowest for TMS and increases for TGS and CTS with the highest values for CTS.

5.4.3 Performance Risk.

Customers investigating complex products are prone to overseeing details, which leads to wrong product choices and malfunctioning (Cyr, Hassanein, Head, & Ivanov, 2007). As noted, a core issue for TMS is the widespread commission-driven sales process, which causes consumer doubts regarding the objectivity of the provided information (Friedman & Srinivas, 2014; Jonietz, Penzel, & Peters, 2015). For example, service employees can easily manipulate decisions by withholding information. Without having other information sources available (i.e. TGS), it is likely that consumers will lack confidence in the performance of the product for TMS. Performance risk further depends on the degree of service and information quality (Grewal et al., 2007; Nicolaou et al., 2013). Following this argumentation, TGS acts as a prerequisite for obtaining valuable information and can further be complemented by TMS as a second instance to verify and fine-tune gathered information (O'Brien et al., 1988; Simon & Usunier, 2007). Combining both therefore diminishes their inherent deficits, with particular relevance of TGS. The CTS process order thus gives consumers time for exploration in order to acquire a detailed product knowledge, and lowers feelings of being pushed to buy a product (Collier & Kimes, 2012). Finally, this leads to the following hypotheses.

H3: The performance risk is highest for TMS and decreases for TGS and CTS with the lowest values for CTS.

5.4.4 Financial Risk.

TMS is sometimes associated with unethical behavior, such as pressuring customers towards products or providing misleading information (Román & Munuera, 2005). This is reinforced by the risk of malfunction of the product (Keh & Pang, 2010) as already mentioned for performance risk and can lead to unexpected costs. Additionally, human-based services such as TMS have generally been shown to be more expensive than SSTs including TGS (Meuter et al., 2000; Selnes & Hansen, 2001). Despite lower cost estimations for TGS, it runs the risk of misunderstanding and overseeing details as well as system failure, for example, cancellation of the transaction or loss of private data (Featherman & Pavlou, 2003). This might increase the financial risk for TGS in certain cases. Nevertheless, as we assume higher financial costs for the product acquisition in TMS to be more present and striking for consumers, TMS is supposed to evoke higher estimations of financial risk. Since CTS incorporates the human component of service, we expect a moderate financial risk for CTS. The following hypotheses are postulated:

H4: The financial risk is lowest for TGS and increases for CTS and TMS with the highest values for TMS.

5.4.5 Time Risk.

While many scholars argue that time savings are the primary motivation to use SSTs (Bateson, 1985), a diverging pattern can be observed for complex products that are infrequently bought via a new channel. This is due to the high amount of information that needs to be considered (Cyr et al., 2007; Maity & Dass, 2014). Therefore, the more service and information cues that are presented, the more search effort needs to be made. Similarly, Simon and Usunier (2007) argue that SSTs reveal more difficulties with interface handling and cannot duplicate all features of a face-to-face communication. For infrequent purchases such as insurance, this implies that a self-engaged product encounter in the TGS condition is deemed to be more time-consuming than a personnel consultation or even delegation of the purchase to an agent in the TMS or CTS conditions. Since CTS comes as partial self-service, an intermediate time risk can be assumed. This leads to the following assumptions:

H5: The time risk is lowest for TMS and increases for CTS and TGS with the highest values for TGS.

5.4.6 Psychological Risk.

When using TMS, customers may experience a loss of control that they can exert on the process and outcome of an interaction (Collier & Sherrell, 2010). Recent studies emphasize the essential role of control as a driver of SST (Bateson, 1985; Ding et al., 2007; Meuter et al., 2000) and a preventer of risks (Grewal et al., 2007). Applied to insurance, given concerns about the unethical behavior of salespeople may cause feelings of low situational influence along with situational discomfort. Together with the concerns about social distance, this drives feelings of psychological risk in TMS. The expected higher financial risk and performance risk further intensify the psychological risks (Keh & Pang, 2010).

TGS therefore enables a flexible and self-controlled product encounter without pressurizing the customer, and sufficient leeway for exploration (Collier & Kimes, 2012). It relieves consumers from contacting a salesperson (Meuter et al., 2000) and concentrates the personnel contact to more difficult concerns (Selnes & Hansen, 2001). Accordingly, it can be expected that this increases the resource matching (Collier & Kimes, 2012) and leads to higher convenience. TGS can further serve to indemnify the information exchange in TMS. Nonetheless, the high need for cognition can conversely intensify psychological risk for TGS (cf. time risk), but is assumed to be less striking compared to TMS. Lastly, the integration of both combines their advantages and reduces their shortcomings. To conclude, the following hypotheses are given.

H6: The psychological risk is highest for TMS and decreases for TGS and CTS with the lowest values for CTS.

5.4.7 M-Commerce Acceptance and Face-to-Screen Service.

Several studies have demonstrated a positive effect of service and information quality on PEOU and PU. Analogous to our prior theorizing, CTS and TGS should thus be most likely to amplify PEOU and PU. Reasons are the extensive sources and information that are provided under high service quality (Maity & Dass, 2014). This enables an efficient decision, and enhances the technological usefulness. High service quality is also marked by high aesthetics of the interface with easy navigation, which generates a high PEOU.

A high information quality enhances the transparency of the process and reduces risks (Nicolaou et al., 2013) leading to higher perceptions of control. Rich information also facilitates learning and understanding of the product and helps users to form new skills and reduce mental effort, reinforcing the ease of use (Ahn et al., 2007). This enhances its own performance by increasing quickness and decision quality, and enables cost savings, leading to more PU (Brown & Jayakody, 2008).

The enhancement of the service and information quality will thus lead directly and indirectly to a substantial increase of the behavioral intention to use the product by improving PU and PEOU and mitigating risks (Kanungo & Jain, 2004; Pavlou, 2003). As noted, CTS best suits the common ROPO behavior and is thus superior regarding the consumers preferences. This leads to the following assumptions.

H7: The PU is lowest for TMS and increases for TGS and CTS with the highest values for CTS.

H8: The PEOU is lowest for TMS and increases for TGS and CTS with the highest values for CTS.

H9: The PI is lowest for TMS and increases for TGS and CTS with the highest values for CTS.

5.5 Research Methodology

5.5.1 Design and Procedure.

The hypotheses were examined in a laboratory experiment in order to control the technology usage assignment and mitigate confounding interferences. The evaluation was undertaken in the research laboratory of a large German university. The study built on a specifically programmed app which was altered slightly for each of four diverging conditions regarding the type of service that was provided. The fix part of the app consisted of a selection of four short-term insurance offers (insurance on a daily basis, e.g. travel insurance or bicycle insurance) presented on the first page. Thereof the travel insurance was selected as a predefined scenario. General information about the previously chosen product (service portfolio, payment, terms and conditions) were presented on a second page. The third page offered a form to enter personal data and payment option, followed by a fourth page with a summary of the service portfolio as well as a “buy now” button. The last site confirmed the successful contractual conclusion and gave an overview over past transactions, the option to report a claim or restart choosing a product from the beginning. This process corresponds to a common and intuitive buying process in e-commerce. To maintain a consistent exploration of the app by the participants, a tutorial video was previously recorded and presented at the beginning of each session. Therein, the main features of the app were visually introduced, accompanied by an auditory explanation, to assure that all participants would experience a common service treatment per condition. At the end of the video, the participants were asked to fill out an online survey to evaluate the app. In total, the experiment, consisting of exposition and survey, lasted 30 minutes. At the end, we included two questions to check the attentive participation of the respondents by asking two app related questions concerning the type of product that was sold and its price. All participants gave the correct answer to question 1 and 98.9% answered question 2 correctly. Therefore, sufficient amount of attention to the experimental conditions was assumed for all respondents.

The four experimental conditions consisted of a (1) Control Group (CG), (2) TMS, (3) TGS and (4) CTS, embedded in the aforementioned sales environment as illustrated in Figure 5.2. To find out which technological service features are favored for the operationalization of TGS, we set a focus group discussion with respect to Kitzinger's (1995) and Mayerhofer's (2007) guidelines. The focus group constituted of seven professionals who had already worked in the field of insurance and m-commerce research. During the discussion, seven areas of TGS features had been prioritized: (1) A summary of the insurance portfolio at the beginning, (2) the implementation of information buttons, (3) the implementation of FAQs, (4) the implementation of a quality assurance seal, (5) the provision of different payment options, (6) an overview over the chosen product specifics before buying and (7) the mailing of the policy and terms and conditions after the contractual conclusion.

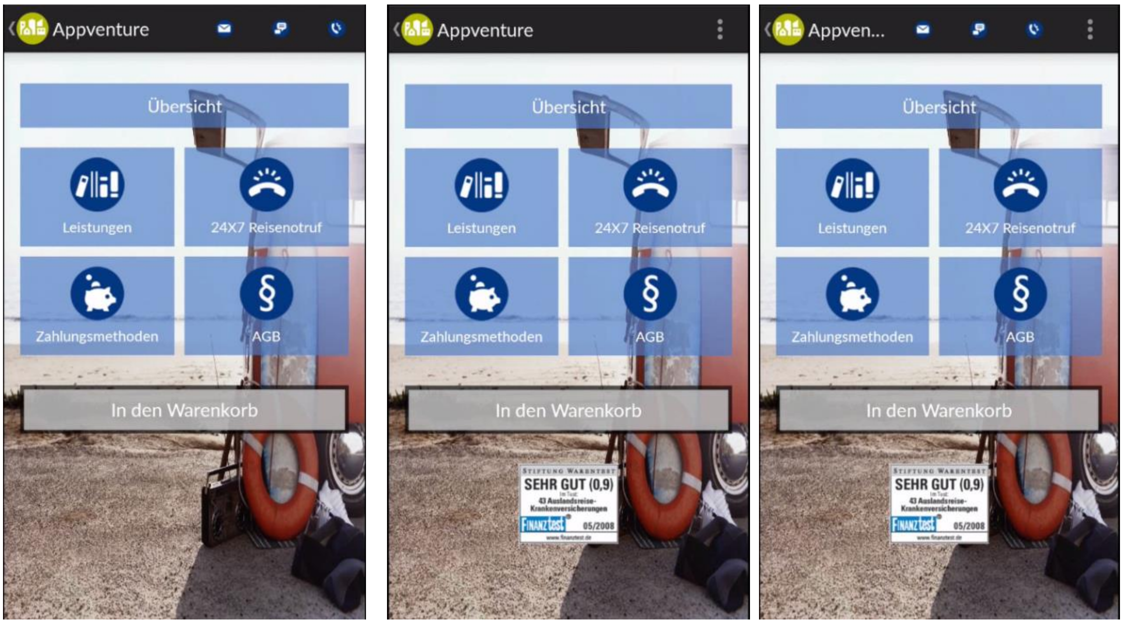

Figure 5.2 The conditions of the experimental design. The conditions TMS (Technology-Mediated Service), TGS (Technology-Generated Service) and CTS (Comprehensive Technological Service) are shown from left to right.

Human service in e-commerce is understood as the opportunity to have access to personnel service via different channels, for instance the availability of an agent's telephone number or e-mail address (Chen & Dubinsky, 2003; Griffith & Krampf, 1998). Froehle (2006) posited that voice telephone calls are today's most frequent means of consumer service communication. He also stated the usage of e-mail and instant messaging (a.k.a. "chat") as the preferred way of consumer encounter. Consequently, we selected the following functions to operationalize TMS: (1) a contact option to call an agent in the locational proximity, (2) a contact option to call an agent at a preferred place (e.g. home town), (3) an e-mail option, and (4) a live chat option. Finally, the CTS condition incorporated all the afore-mentioned features of TMS and TGS in one app. A control group with no service features, but the basic app design and functionalities, was additionally implemented in order to verify the effectiveness of our treatment.

5.5.2 Sample.

Each participant was rewarded with 8 Euros for their participation. All participants were randomly assigned to one of the conditions. We considered a student sample as the relevant target group for service-based m-commerce, as they are likely to be familiar with mobile devices, as well as the internet as a medium for communication and commercial transactions (Cyr et al., 2007). In total, 188 participants took part in the experiment[15] with an average age of 24.3 (SD = 6.8; MD = 23.00) and a distribution of 108 females and 80 males. To cleanse our data, we first controlled for outliers. To detect abnormal response patterns, we calculated the distance of each case to the centroid of all cases given in Mahalanobis-d squared. It indicates outliers, but should be followed by an logical and individual assessment of each case (Ostrom & Iacobucci, 1995). We thus skimmed all those cases by hand for conspicuous patterns. We dropped three cases due to an abnormal response behavior (e.g. one value for all items), but kept all other outliers in order not to exclude extreme positions. Moreover, we excluded all respondents with an age that was more than three standard deviations beyond the group mean (~ extreme values). This was done to take into account multiple studies showing that older people (above 50) are more reluctant towards new technologies (Dean, 2008; Meuter et al., 2005; Simon & Usunier, 2007). Reasons can be seen in the lower confidence, less experience, greater anxiety and need for human interaction and attribution of more selfish corporate motives for the introduction of SSTs in this cohort (Curran et al., 2003;

[15] The data evaluation of this study was partly conducted together with Nora Müller and Dr. Christian Matt in context of her master thesis, which was supervised by me and Dr. Christian Matt.

Dean, 2008; Morris & Venkatesh, 2000). In total we dropped another five cases. The final sample consisted of 180 participants (Table 2) with an average age of 23.47 (*SD* = 4.38, *MD* = 23.00). An ANOVA for age and a χ^2-test for gender, education and income level revealed no significant distribution differences between any of the groups[16]. A detailed demographical profile is shown in Table 5.2.

Table 5.2 *Profile of Respondents.*

	CG	TMS	TGS	CTS	Overall
Number of Respondents	44	46	47	43	180
Gender					
Male	17	20	18	21	76
Female	27	26	29	22	104
Age					
18-19	9	3	2	8	22
20-29	31	43	40	33	147
30-39	4	-	4	-	8
Over 40	-	-	1	2	3
Average	22.8	23.2	24.2	23.2	23.4
Education					
High school	34	32	34	33	133
Graduates (Bachelor or Master)	10	14	13	10	47
Income					
<1001€	37	43	35	33	127
1001 – 2000€	6	2	8	8	24
2001 – 3000€	1	1	2	-	4
3001 – 4000€	-	-	-	-	-
4001 – 5000€	-	-	1	1	2
>5000€	-	-	1	1	2

Notes. CG = Control Group, TMS = Technology-Mediated Service, TGS = Technology-Generated Service, CTS = Comprehensive Technological Service.

5.5.3 Measures.

In our study we used validated multi-item scales with minor changes in the wording to better match the m-commerce scenario. All items were measured on a 1-7 Likert-type scale with an anchor of 1 for “strongly disagree” to 7 for “strongly agree”. The items were translated into German by using the process of item-equivalence (Brislin, 1970). This means all items were translated by a bilingual person from English into German and backwards by a second bilingual person. Differences concerning the wording were discussed and solved by the translators in coordination with the authors in the final step. For an item overview see Appendix 8.7.

[16] We later repeated the comparisons regarding the group homogeneity for our exploratory analysis with the age-reduced dataset. The results revealed no significant difference between the groups.

To measure the constructs of service quality and information quality we adapted 6 plus 7 of the items used by Ahn et al. (2007). PU and PEOU were examined by adjusting common items widely established in the literature (Ahn et al., 2007). These variables were measured by seven items each. The amount of perceived risk was assessed by adapting scales from Stone and Grønhaug (1993), Jarvenpaa and Todd (1996) and Featherman and Pavlou (2003) as used by Crespo et al. (2009). These scales consisted of four items for performance risk and three items for all remaining risk dimensions. Finally, for purchase intention a three item scale used by Kozup, Creyer, and Burton (2003) was adjusted to our context. A first pretest under inclusion of 10 persons that were working in the insurance business was conducted in advance in order to guarantee a clear understanding of all items. In this pretest both video and questionnaire had to be checked. After fixing all major issues, a second pretest with 10 respondents consisting of students and research employees was carried out and a comprehensible version finalized.

5.5.4 Model Fit.

We initially tested the data for internal reliability, convergent and discriminant validity next to normal distribution and variance homogeneity. We conducted a confirmatory factor analysis (CFA) by using structural equation modeling (SEM) with maximum likelihood estimation. Herein, larger sample sizes are likely to obtain more robust estimations (Hair et al., 2013; Ostrom & Iacobucci, 1995). We therefore incorporated all four conditions in one measurement model and used the initial dataset containing all 188 respondents. To avoid issues in the evaluation or the reduction of the set of fit statistics that is provided, we previously controlled for missing data. In total there were four missing values in the dataset. Due to this small amount (below 0.0003% out of all values) and their random distribution, we applied a simple mean substitution to finally utilize all gathered information. The analyses were done with IBM AMOS® 22. Firstly, we calculated Cronbach´s alpha and the item-to-total correlations to test the reliability. All alpha values ranged between .72 and .92 and thus exceeded the recommended threshold of .70 (Nunnally, 1978). Further, all items surpassed the commonly used threshold of .30 for the item-to-total correlation (Nunnally & Bernstein, 1994) with a range of .51 to .90.

Secondly, convergent validity was investigated by calculating the average variance extracted (AVE), composite reliability (CR) and factor loadings of the items. For the test, statistics values beyond .50 for the AVE and .60 for the CR are recommended (Bagozzi & Yi, 1988; Fornell & Larcker, 1981). In accordance, all AVE values of the variables surpassed the value of .50, with a range of .50 up to .81. The CR values ranged between .77 and .93 and thus exceeded the recommended threshold. For the factor loadings we followed the common guidelines (Hair et al., 2013), suggesting that the standardized loadings should all be significant and above .50 or ideally above .70. Referring to this, we kept items above .50 in the analysis. Of the used 43 items 34 had excellent factor loadings ($\beta > .71$ or .63), and four items had fair loadings with a value above .50. The remaining five items were dropped from the analysis, so that a final sample of 38 items resulted.

Thirdly, to test the discriminant validity in a next step, we used the Fornell-Larcker criterion. The square root of the AVE exceeded the interconstruct correlations in every case. Last, we assessed the goodness of fit for our structural model by using the procedures as recommended for samples with less than 250 participants (Hair et al., 2013) and more than 30 indicator variables. Those are values above .92 for CFI and TLI, values below .08 for RMSEA and below .09 for SRMR. In total, the model revealed an acceptable model fit: $\chi^2(602) = 910$, $\chi^2/df = 1.5$, RMSEA = .052, CFI = .93. Finally, the robustness of our measures obtained evidence through confirmed internal consistency, convergent and discriminant validity as well as a satisfactory model fit. A summary of all values can be found in Appendix 8.8.

Additionally, we tested our data regarding normal distribution and multicollinearity. The test statistics in AMOS® revealed a violation of the normal distribution. Nevertheless, the values for skewness were below 3 and for kurtosis below 10, which is acceptable according to Kline (2005). Moreover, parametric tests have proven to be robust against deviations in the normal distribution with increasing sample size (Hair et al., 2013). The collinearity was tested by calculating the variance inflation factor for all independent variables. All values were below 3.1 and accordingly did not exceed the given threshold of 5.0 (Hair et al., 2013). Taking all together, the gathered data are thus adequate for employing parametric tests.

5.5.5 Common Method Bias.

The usage of a single methodology to evaluate data carries the risk of generating common variance over all factors caused by the common method. To control for this common method bias (CMB), we followed Podsakoff et al. (2003) recommendations to implement structural remedies, for instance contextual information, descriptions to reduce uncertainty and guaranteed anonymity of the participants. The application of Harman's single-factor test in complementation with the Marker Variable Technique has widely established to control for a severe CMB (Lindell & Whitney, 2001; Podsakoff et al., 2003). The first constitutes that

CMB is prevalent when more than 50% of the covariance among all items can be explained by one common factor. Applied to our data, one factor explained 29.93 % of the variance over all measures in a principal component analysis. The marker variable technique further tests how much variance a common latent factor (CLF) can explain all items under the inclusion of a seemingly uncorrelated marker variable. To build an independent marker variable, we used a combination of three scales in order to isolate the amount of common variance. Items were extracted from scales measuring the amount of innovation resistance, perceived tradition barrier in innovation acceptance and perceived image barrier towards insurance. All three measures had the same Likert-scale format. The outcome revealed a common variance of 3.24% overall items. Thus CMB does not appear to be a serious threat for the interpretation of our data.

5.5.6 Manipulation Check.

To verify that our manipulation was successful with a notable difference in the perception of technology-mediated and technology-generated service, we implemented the following two questions: (1) “How do you rate the service offered by personal counseling in the app” (very low to very high), (2) “How do you perceive the service given through functions like summaries and payment options?”. For question one, a t-test showed that the TMS condition (M = 4.59) revealed a significant higher value than the TGS condition (M = 3.26; $t_{(91)}$ = 4.42, p < .01) and the CG (M = 3.57, $t_{(88)}$ = - 3.17, p < .01), while the TGS and the control condition did not differ significantly ($t_{(89)}$ = 1.01, p = .32). Thus the effectiveness of the implementation of human service was supported.

For question two, it was shown that the TGS condition had the strongest incline in the perception of technological service (ΔM = 1.67, $t_{(46)}$ = 6.56, p > .01, d = 1.22) compared to question one, while TGS had the smallest incline (ΔM = 0.73, $t_{(45)}$ = 3.67, p < .01, d = 0.52). However, the implementation of technological components also amplified the perception of TMS, so that TGS and TMS did not differ significantly ($\Delta M_{TMS\text{-}TGS}$ = 0.39, $t_{(91)}$ = 1.40, p = .17). This might be due to some interpretation leeway regarding the item, for example, construing the policy as summary or free imagination of service when TMS is given. Nevertheless, the strong increase in TGS supported an effective manipulation. Lastly, CTS as combination should have equal values as TMS for the first item and equal values as TGS for the second one. Both assumptions were supported by insignificant differences ($\Delta M_{TMS\text{-}CTS}$ = - 0.13, $t_{(87)}$ = 0.44, p = .66; $\Delta M_{TGS\text{-}CTS}$ = - 0.51, $t_{(88)}$ = - 1.99, p = .05). In total the manipulation was effective.

5.6 Results

To validate our hypotheses, we calculated multiple trend tests by using orthogonal contrast analyses. Compared to ANOVA contrasts provide the advantage of not only testing the treatment differences for significance, but also specific predefined directions. Therefore, lambda-weights are assigned according to the a-priori defined hypotheses, which totals to zero. For Hypothesis 1 and 2, this leads to the contrast weights of TGS 1, CTS 2 and TMS -3, indicating a superiority of the second. To obtain the 5% alpha level for directed hypotheses, the 90% alpha confidence interval was taken as the decisional basis. This means that a hypothesis is supported, when the exceedance probability is below .10. A summary of the means of all constructs four each condition is shown in

Appendix 8.9.

As hypothesized, the treatment with TGS and CTS revealed a significant higher service quality compared to TMS, with the highest value for CTS ($F_{(1,176)} = 3.76$, $p < .10$, $\eta^2 = .021$). Thus hypothesis H1 was supported. Analogous to service quality, the contrast analysis revealed a significant effect of small to medium effect size for information quality ($F_{(1,176)} = 4.48$, $p < .05$, $\eta^2 = .025$) with the highest values for CTS. Thus, the results supported H2.

In Hypothesis H3 we stated the superiority of CTS regarding the perceived performance risk and a maximized risk for TMS. This was tested by calculating a contrast in the form 3, -1 and -2 for the order TMS, TGS and CTS. In terms of risk lower contrast weights represent less risk perceptions. The predefined trend was significant with a small effect size ($F_{(1,176)} = 3.51$, $p < .10$, $\eta^2 = .020$). Thus the Hypothesis H3 was supported. In H4 we assumed TMS to generate the highest perceptions of financial risk and decreasing values for CTS and TGS with lowest values for the latter. Therefore, we tested the trend with the coefficients 3, -1, -2 (~TMS, CTS and TGS). This trend was confirmed by the data ($F_{(1,176)} = 4.94$, $p < .05$, $\eta^2 = .027$) and revealed a small size effect. Conclusively, H4 was supported. For H5 involving the time risk we postulated a superiority of TMS and an increase for CTS and TGS with the highest value for the TGS (contrast weights: TMS -2, CTS -1, TGS 3). The overall trend revealed a significant result ($F_{(1,176)} = 3.72$, $p < .10$, $\eta^2 = .021$). In conclusion, the hypothesis H5 was supported by the data. *H6 postulated that TMS causes the highest perceptions of psychological risks while CTS causes the lowest values* (contrast weights: TMS 3 TGS -1 CTS -2). The data analysis gave support for this assumption ($F_{(1,176)} = 11.95$, $p < .01$, $\eta^2 = .064$) with an effect of medium effect size. In turn H6 was confirmed.

We next tested the superiority of CTS for PU and PEOU as hypothesized in H7 and H8. Contrary to our hypotheses the effect for PU ($F_{(1,176)} = 0.15$, $p = .70$) as well as for PEOU ($F_{(1,176)} = 2.26$, $p = .13$) were not significant. Therefore, both hypotheses were rejected. A subsequent exploratory contrast analysis was conducted to test a single superiority of CTS over both variables. For PU no significant difference between CTS and the remaining groups was found ($F_{(1,176)} = 0.03$, $p = .86$), but CTS revealed a significant higher EOU in relation to all other conditions ($F_{(1,176)} = 10.303$, $p < .01$, $\eta^2 = .055$).

Finally, we postulated a positive impact of the combined service condition (CTS) on the intention to purchase a mobile insurance. The results did not reveal a coherent support for this assumption. Though CTS ($M = 4.12$) was the only value above 4[17] and considerably exceeded the TMS condition ($\Delta M_{CTS\text{-}TMS} = 0.52$; $F_{(1,176)} = 2.04$, $p = .16$) and the CG ($\Delta M_{CTS\text{-}CG} = 0.35$, $F_{(1,176)} = 0.93$, $p = .34$), the effects did not obtain significance. The postulated trend in H9 could not be confirmed ($F_{(1,176)} = 2.04$, $p = .16$). A summary of the hypotheses outcome is shown in Table 5.3.

Table 5.3 *Hypotheses Summary.*

Hypotheses	**Variables**	**Contrast Weights**	**Result**
H1	Service Quality	-3 1 2 [a]	Supported
H2	Information Quality	-3 1 2 [a]	Supported
H3	Performance Risk	3 -1 -2 [a]	Supported
H4	Financial Risk	3 -2 -1 [a]	Supported
H5	Time Risk	-2 3 -1 [a]	Supported
H6	Psychological Risk	3 -1 -2 [a]	Supported
H7	Perceived Usefulness	-3 1 2 [a]	Not Supported
H8	Perceived Ease of Use	-3 1 2 [a]	Not Supported
	Perceived Ease of Use	-1 -1 2 [ab]	Supported
H9	Purchase Intention	-3 1 2 [a]	Not Supported
	Purchase Intention	-3 1 2 [abc]	Supported

Notes. [a] Orthogonal contrast coefficients in the order TMS, TGS and CTS. [b] Additional exploratory analysis. [c] Exclusion of 18-19 year cohort

It is noteworthy that we found high standard deviations for purchase intention, ranging from 1.52 to 1.81. In consequence, we extended the investigations in an exploratory fashion by distinguishing different age groups. This seemed reasonable, since scholars have already argued that past experience with a seller or product alters the purchase intention

[17] Since 4 is the scale mean, this can be seen as critical threshold for purchases to take action. This is in line with findings by Gefen and Pavlou (2012)

(Gefen & Pavlou, 2012). With regard to insurance, the experience level of consumers grows in strong relation to different life phases. Therefore, young people who are just starting into a self-determined life are low in insurance experience and should thus reveal a divergent pattern. The exploratory analysis supported this assumption, by showing a significant interaction effect between age and treatment group ($F_{(3,\ 169)} = 3.23$, $p < .05$, $\eta^2 = .054$), when splitting the sample into two groups by the age of 21 (18 to 21, $n = 72$ vs. 22 and older, $n = 108$). Even a subsequent exclusion of the cohort of 18-19 year old respondents ($n = 22$) turned H9 into significance ($F_{(3,\ 169)} = 3.79$, $p < .1$, $\eta^2 = .024$). Eventually, we found partial support for our hypothesis setting CTS as the superior condition regarding purchase intention. Figure 5.3 and Figure 5.4 illustrate the identified trends for all variables.

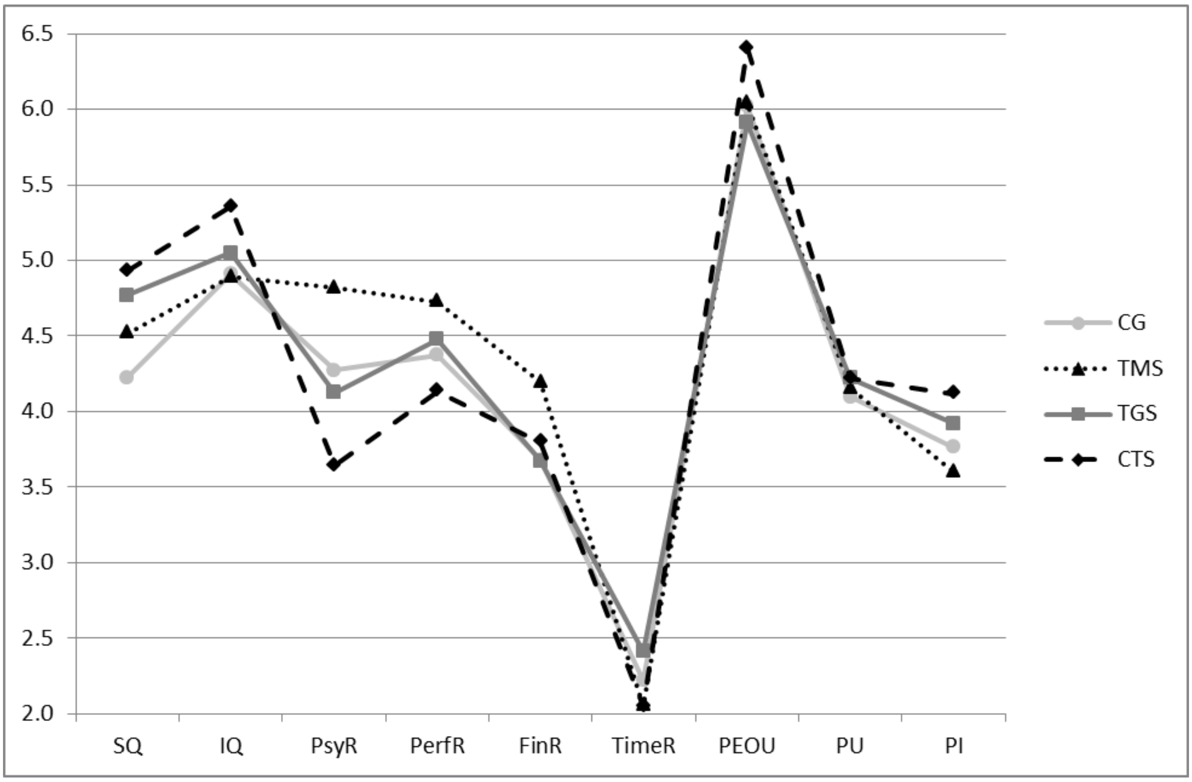

Figure 5.3 Mean values of the different service types. FtoS = Face-to-Screen, CG = Control Group, TMS = Technology-Mediated Service, TGS = Technology-Generated Service, CTS = Comprehensive Technological Service, SQ = Service Quality, IQ = Information Quality, PsyR = Psychological Risk, PerfR = Performance Risk, FinR = Financial Risk, TimeR = Time Risk, PEOU = Perceived Ease of Use, PU = Perceived Usefulness, PI = Purchase Intention.

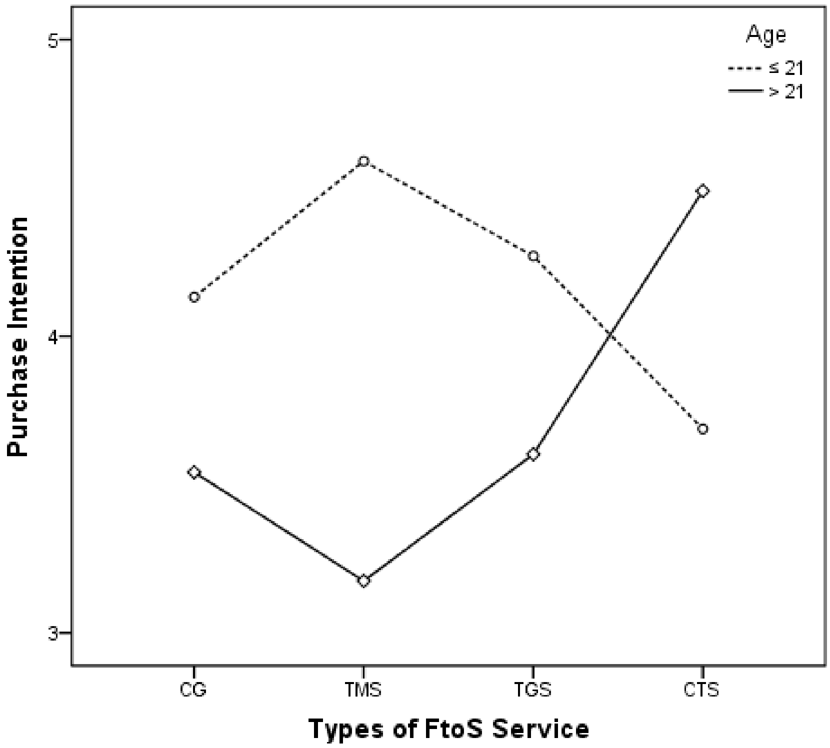

Figure 5.4 Interaction effect of age groups with type of FtoS service. FtoS = Face-to-Screen, CG = Control Group, TMS = Technology-Mediated Service, TGS = Technology-Generated Service, CTS = Comprehensive Technological Service.

5.7 Discussion

The present study is the first in IS research that examines different types of service in m-commerce to leverage the adoption of complex products. As a key outcome, we provide new insights into the mechanisms determining consumers' need for specific configurations of service in m-commerce. The results substantially extend the knowledge about FtoS service in order to enhance the willingness to buy complex products via mobile devices. This was realized by integrating TMS and TGS in order to level the disadvantages of both of them. Our investigations showed that TGS, as well as CTS, fosters a positive estimation of service quality with the highest influence of the second. CTS likewise revealed a positive impact on information quality and significantly lowered the perceived performance risk in contrast to TMS. This implies that a combination of the services is inevitable to reduce the estimation of hazards experienced through product malfunctioning. It was further shown that the highest financial risk is caused by the human-based TMS, while the technical service rendered the lowest perception of financial risk. As argued, this gives rise to the assumption that human components in service provision engender higher cost estimations. On the other hand, TGS was found to reveal the highest values for time risk among all groups. This supports the divergence of self-services for complex products in m-commerce from simple retail as it causes higher time effort concerns. Moreover, TMS was found to reveal the highest psychological risks, while CTS revealed the lowest. Both variables differed significantly. This result supports the hypothesized increase of discomfort and inconvenience by the integration of TMS. TGS therefore did not substantially alter the perception of psychological risk as it performed on the level of the control group. Although, PU, PEOU and PI had not been influenced by the type of service in a first investigation, subsequent analyses confirmed a general positive increase for PEOU and PI leveraged by CTS under exclusion of the age group of 19 and younger. The results substantiate our assumption about consumers' preference for mere technological service if they have the choice between TMS and TGS. Nonetheless, they value even more the integration of human components as a second-instance assurance. To summarize, all hypothesized effects were in the predicted direction, and mainly corresponded to the presented theorizing. It can be noted that higher order effects (i.e. interactions) are found to play a crucial role, as shown for the example of age.

5.7.1 Theoretical Implications.

The present research obtained valuable contributions for the enlightenment of mechanisms determining the adoption of m-commerce by utilization of FtoS service. There are five major implications for theory: Firstly, prior literature revealed discordance about the benefits of technology service usage as an augmentation to personal service encounters (Dabholkar, Michelle Bobbitt, & Lee, 2003; Giebelhausen et al., 2014; Meuter et al., 2003; Meuter et al., 2000). While some studies found mainly positive relations (Bitner et al., 2000; Salomann, Dous, Kolbe, & Brenner, 2007) others indicated a more complex pattern including negative effects as well (Giebelhausen et al., 2014; Keh & Pang, 2010; Meuter et al., 2000). Our results support a differentiated view of service migration in FtoS contexts and provide evidence that personal service can even inhibit the adoption of m-commerce under certain conditions. In this relation, our research attenuates the importance of personnel service in m-commerce and accentuates the role of technological service as a respite from service encounter. The findings further implicate that there standard formula for the appropriate deployment of personnel and technological service, but the need for a thorough balancing of both. This corresponds with Dabholkar's (1992) recommendation to generally provide consumers with full service options.

Secondly, this study adds depth to the understanding of the psychological mechanisms that are affected by FtoS service. The results leverage previous findings, supporting the importance of service and information quality as effective means in order to reduce uncertainties during the decision process (Grewal et al., 2007; Mitchell & McGoldrick, 1996; Nicolaou et al., 2013; Sweeney et al., 1999). It is suggested that service quality in the product encounter prior to the purchase can predominantly be enhanced by elaborating on TGS. However, this carries the risk of high time effort. In contrast, TMS alone revealed detrimental effects on performance risk, financial risk, and psychological risk. Our findings offer new knowledge of how to counteract against these mechanisms, as often requested in the literature (Crespo et al., 2009; Gefen & Pavlou, 2012; Keh & Pang, 2010; Pavlou, 2003). The insights support the need for CTS as a requirement of high PEOU and purchase intention, but do not affect PU.

Thirdly, the suggested concept of STTF gained support by an increase of service quality, information quality, ease of use and purchase intention as well as the reduction of psychological and performance risk perceptions under the condition of highest predicted STTF (CTS). This extends recent theorizing about the issue of coherence (in terms of fit) for the acceptance of IS (Goodhue & Thompson, 1995; Maity & Dass, 2014; Negahban & Chung, 2014). Our results satisfy the demand for more research in information and service provision (Curran & Meuter, 2005; Froehle, 2006).

Fourthly, the vast majority of studies in this area has placed a strong focus on the moment of personnel service interaction, but disregards the initial contact with the sales technology (Froehle, 2006; Giebelhausen et al., 2014; Gremler & Gwinner, 2008). We purposely joined this relevant moment in m-commerce where adoption rates for complex products are yet fairly low, by taking the prototypical first approach towards a sales app, and excluding the actual encounter to service staff when using TMS. This enables coherent conclusions about the initial decision process as shaped by the service elements in an app. From a theoretical point of view, the results suggest designing the service alongside the decision chain (e.g. ROPO) determined by the type of product. This is in line with current decision making models (Karimi et al., 2015), and contributes by giving more tangible insights into how to match consumers' decision steps with the service design. More specifically, initial decision steps such as the need for recognition, information search, and evaluation of alternatives should be well covered with TGS. Later process steps such as the thorough product research and appraisal are characterized by more complexity and thus increase the need for human interaction as provided by TMS. These insights help to reduce over-blown technologies leading to frustration and irritation (Hausman & Siekpe, 2009).

Lastly, our results obtained an exploratory insight into demographical differences with regard to the preference for types of service in m-commerce. By taking into account the complexity of insurance, experienced-related factors (i.e. age, self-efficacy, product knowledge) seem to alter the preference for the service that is received. This is in line with several findings. According to Maity and Dass (2014) low or no product knowledge increases the need for TMS as complexity is rising. In turn, TGS may profit from the decrease of complexity with increasing product knowledge. Likewise, Gefen and Pavlou (2012) argue that risk declines in influence when the institutional structures are perceived to be poor. Perhaps young and unexperienced consumers do not even take the transaction into account, resulting in indifference regarding the risk estimation regardless of the condition. This is supported by the significant difference in the result for the older age group regarding performance risk and purchase intention. However, findings in this area vary according to the sample extract that is acquired (Liébana-Cabanillas et al., 2014). Considering age differences on a small scale perhaps discloses opposing patterns regarding technology acceptance compared to considerations on a big scale. To make reliable predictions, research should thus take care for substantial life cycle changes (e.g. in a long-term study) and different age groups within the sample.

5.7.2 Practical Implications.

Our results have important implications for companies that deal with sales of complex products to end users. First, the results suggest placing more priority on TGS as a proper alternative to personal interaction. This is necessary in order to encourage consumers for a self-determined purchase or even for indemnifying a misleading personal contact.

Secondly, the results reveal a considerable need to enhance the trust in the sales process as indicated by the ROPO behavior. This can be achieved by providing consumers with sufficient mobile self-service options, complemented with the support of ethical trained stuff (McClaren, 2013). Sales commissions should more often be turned into service commissions, which means basing commission on customer satisfaction rather than sales. This can be realized by implementing a rating system in m-commerce which evaluates a consumer’s impression subsequent to the service contact. This will help to reinforce the trustworthiness of salespeople in the insurance industry.

Third, m-commerce should be designed consistent to common decision processes of consumers (Rogers, 1995). Each page needs to be scanned for emerging risks and treated by adding technological or personal service elements. However, the amount of available features to establish a sophisticated technological service is manifold (Hausman & Siekpe, 2009), but still entails great potential for the future. The implementation of artificial intelligence, for example chatbots and avatars as advisor (cf. virtual agents), could improve the service experience of consumers and relieve service personal.

Finally, our results confirmed considerable differences between different age groups, suggesting that service adoption varies along with the amount of product experience and other individual characteristics (Devlin, 2007; Froehle, 2006; Grewal, Krishnan, Baker, & Borin, 1998). The accentuation of human interaction should thus differ according to the experience level a consumer states. These insights are particularly important, since they can help to overcome given deficits in the perceived provider benevolence in m-commerce (Ball, Coelho, & Vilares, 2006).

5.7.3 Limitations and Future Research.

Our research contains limitations which provide opportunities for future research: Owing to our labor-intensive experimental procedure the sample size was fairly moderate. Due to this we were not able to analyze differences across the factors such as age, or experience in greater detail. This gives rise to a more detailed investigation of demographical, sociographical and cultural attributes. For example, Ward and Lee (2000) pointed out that novice consumers rely more strongly on reputation and brand names compared to experienced consumers. The result may explain the difference for young respondents, but needs more evidence to give concrete implications for the TGS and TMS balancing.

To our knowledge there is no classification of the value of different service features regarding technology adoption. The influence of FAQs, search function, assurance seals etc. may vary in terms of their effect on technology adoption. This can be augmented by also taking brand labels into consideration, as one of the main determinants in increasing trust and purchase intention (Featherman & Pavlou, 2003; Grewal et al., 1998; Ruparelia et al., 2010). It can likely be expected that well-known brand names moderate the need for TGS and TMS in particular. We therefore suggest a detailed investigation of the effects of different service features in future research.

Our results gave valuable insights for financial services such as mobile insurance or mobile banking but accounted only for a single product category. We did not distinguish between search goods, experience goods and credence goods or between hedonic and utilitarian goods. This comparison may have led to considerable differences regarding the arrangement of FtoS service and should thus be subject to future investigations. We also considered short-time insurance, which possess less complexity than life insurance for instance. It thus can be presumed that even different levels of product complexity alter the need for interaction. This shortcoming has to be addressed by future research.

As noted, we focused on the pre-purchase contact with the sales technology, but disregarded the concrete personal interaction in this process. Future studies should further elaborate on customers` experience and behavior along the entire purchase process including post-purchase and repeated purchase behavior.

5.8 Conclusion

The presented research revealed initial solutions to the lack of service in m-commerce. We pointed out that human-based service in face-to-screen environments is insufficient to satisfy consumers' needs. Reasons can be seen in the lack of fit between the type of service and the task-technology combination. It was shown that m-commerce requires a high amount of technological service in order to improve the perceived service quality and mitigate risks. In combination with the provision of human-based service components this so-called comprehensive technological service finally served to leverage purchase intention. In consequence, this article encourages service providers to elaborate on the technical component of service in m-commerce while maintaining existing human assistance and thus shaping a comprehensive and seamless service environment. However, our research suggests further influencing factors moderating the relationship between type of service and behavioral intention. In this vein, age was posed as a relevant determinant, which appears to change the preferences for m-commerce in a moderating fashion. To summarize, these results reinforce a case-by-case configuration of mobile service to satisfy the individual consumer's need for the service-task-technology fit.

6 General Discussion

6.1 Summary

The central objective of this thesis was to obtain a comprehensive understanding of the mechanisms that underlie m-commerce resistance for complex products and to offer countermeasures that could mitigate the adoption inertia. This thesis addressed prevailing research gaps concerning the *sources of m-commerce resistance* and the *means to merge insurance and m-commerce*. A series of four studies was conducted to achieve this. In the following text, the main findings are summarized.

In **Study 1** we investigated the psychological mechanisms that determine channel choice to answer why complex products appear to be less suitable to m-commerce and why people with higher product expertise show higher values of resistance. In line with the ECT, it was found that channel choice with regard to agents, e-commerce and m-commerce results as a function of the complexity-service fit. This supports that consumers pre-assess both the service level and the complexity level of each product prior to purchase. The higher the complexity, the more service performance is expected. Consumers therefore preferred the channel where service and complexity were most balanced and confirmed their expectations. For agents, products with high complexity revealed the highest purchase intention, while for m-commerce the low complexity products were preferred. By drawing on both the ECT and status quo bias theory it was further shown that consumers with extensive expertise display stronger ties to the high service channel and less ties to low service channels compared to people with less expertise. The latter were accordingly less rigid regarding the selection of a channel. Lastly, by combining knowledge from the ECT, status quo bias theory and ELM it was demonstrated that the impact of complexity on risks varies in dependence of the product expertise of each consumer. Expertise moderated the association between complexity and risk. Complexity has a greater influence on the channel choice decision for people with high expertise compared to medium and low expertise. This explains higher switching barriers as observed for consumers with extensive expertise.

In **Study 2** we aimed to increase the understanding of the sources of resistance in m-commerce by identifying the underlying barriers with a means-end approach. This answers questions about problematic attributes for the adoption of m-commerce and uncovers underlying mechanisms. The implication matrix revealed 15 ladders of high priority, with four significant origins of m-commerce resistance, including poor ergonomics, payment concerns, no service advice or support, and uncertain data handling. This highlights service and system quality as the primary source of resistance, followed by information quality. The most salient chain was found for poor ergonomics, which most likely conflicts with the value of convenience. Moreover, a high salience was found for the missing service advice and support, which was reported to restrict the desire for convenience. Missing service and advice as well as payment concerns were among the most-often cited obstacles in terms of performance and economy. In addition, consumers were apprehensive about data handling in m-commerce, and feared the loss of convenience and secure privacy when facing an m-insurance purchase. The main mediators between the attributes and values were an increasing personal effort and the related time investment.

In the course of **Study 3** we examined the potential of service quality to mitigate emerging risks in course of m-commerce usage for complex products. This answered the question of the ability of service to counteract risks, to improve the purchase intention in m-commerce, and to what extent it is needed to reach the best outcome. Building on a set of four supplementary analyses, we first investigated the impact of service and information quality on risk, including the five dimensions of privacy, performance, finance, time and psychological risk in a structural equation model. Service quality was found to have a substantial direct and indirect effect on purchase intention, mediated through risk and information quality. We further specified the intra-structure of the mentioned risks, which supported high interdependencies, capturing performance risk as a primary trigger of the other risk dimensions and psychological risk as a second-order hub which concentrates the effects of the remaining risk dimensions. Therefore, the proposed differentiation into concrete risk dimensions that coalesce to more abstract risk dimensions was confirmed. We further demonstrated that increasing service quality steadily increases the purchase intention in m-commerce except for levels of low risk. It was found that risk is most likely to enter the purchase decision for modest levels of service quality, but decreases for high and low service quality, delineating a moderation of quadratic fashion. For consumers with low risk perception, an overinvestment of service quality was shown to reduce the purchase intention. In a last step, a between-group design affirmed these results by revealing significant differences in the influence of risks for the high and low service quality condition.

In **Study 4** we investigated the configuration of different types of face-to-screen (FtoS) service in m-commerce to support m-commerce adoption for insurance. This answered how service in m-commerce needs to be designed to facilitate an effective purchase. In a laboratory experiment participants were exposed to different types of service, including technology mediated (TMS), technology generated (TGS) and comprehensive technological service (CTS) as a hybrid approach, which combined TMS and TGS. The results substantially contributed to the knowledge about FtoS service and are among the first which encountered the configuration of service types in m-commerce. Drawing on theorizing from the task-technology fit literature and the trend towards a ROPO behavior, it was shown that neither TMS nor TGS alone are capable of eradicating m-commerce resistance in the insurance business. However, with the exception of time risk, TGS had a more positive effect on the remaining risk dimensions compared to TMS. When merging both service types in CTS, consumers' perceived the highest service and information quality and the lowest risk. Assumptions that this fosters the purchase intention did not hold true for the overall sample, except for consumers' above the age of 19. The results provide evidence for the need to align service to the requirements of the task and the technology, which we termed as service-task-technology fit.

6.2 Implications

6.2.1 Theoretical Implications

The obtained theoretical achievements in this thesis advance the IS literature in a number of different ways. In the following, the main contributions are summarized and integrated into an overall picture. The theoretical impact of this thesis can be summarized in five central achievements.

Firstly, we advanced m-commerce research by *showing the importance of fit*, based on four fundamental theories, namely the expectation-confirmation theory, status quo bias theory, elaboration likelihood model and task-technology fit theory. Our findings indicated that resistance is based on an actual existing misfit between service, task and technology in m-commerce, as described by the ECT. This is aggravated for consumers with high product expertise, caused by an extended information processing and occurring perception biases as defined by the elaboration likelihood model and the status quo bias theory. The need for fit was further underpinned by creating successful combinations of technological types of service to launch a fit between service, task and technology. The outcome confirmed the advantages of the fit assumption and supported the requirement of a Service-Task-Technology Fit as cornerstone to m-commerce success. This contributes to literature, since it puts separate findings into a bigger picture (Maity & Dass, 2014; Simon & Usunier, 2007) and adds new thoughts to enhance the argumentations (Özpolat et al., 2013).

Secondly, we *encountered the criticism on the oversimplified* nature of past research approaches in the IS literature (Brown et al., 2012; Edwards, 2002; Gefen & Pavlou, 2012; Venkatesh & Goyal, 2010). Therefore, insights gained through common quantitative methodologies such as ANOVA and SEM were elaborated by posing higher order relations, tested in the frame of polynomial equation modeling and response surface analyses. Although under-utilized, higher-order functions allow better descriptions of the fundamental processes and by displaying changing effects for different manifestations of the variables. This solves some incongruence about the role of complexity, by identifying product expertise as a reason for deviant findings (e.g. (Maity & Dass, 2014; Simon & Usunier, 2007). Similarly, we proposed the risk level in a purchase process to determine the amount of consumer service that is required. This concretizes findings which stress the problem of service overinvestment (Gefen & Pavlou, 2012; Özpolat et al., 2013). Supplementary to the quantitative considerations, the qualitative means-end approach was applied to obtain tangible and profound results which underpin the abstract relations found in the quantitative investigations. The suggested mixed-method research follows the call for elaboration of the dominating quantitative insights into IS research (Coursaris & Kim, 2011; Hoehle et al., 2012) and provides methodological guidance to promote comprehensive empiricism in the future.

Thirdly, our research *introduced, adjusted and referenced constructs in m-commerce* that have proven relevancy to explaining consumer behavior in traditional channels, but were rarely transferred to mobile environments. These constructs are primarily: complexity, perceived risk, service quality and information quality. Consistent with prior findings, it was confirmed that product complexity strongly affects the choice for m-commerce (Balabanis et al., 2006; Maity & Dass, 2014; Simon & Usunier, 2007). Its effect is mediated via several risk dimensions which lower the intention to purchase mobile insurance. In this thesis we further extended previous insights by combining research on m-commerce “disabler” and “enabler”. Through this, our work established service quality as an effective means to reducing the negative effects of complexity and risks. The drawn associations follow the demands of the literature to deepen the understanding of channel choice and switching barriers in order to facilitate the adoption of new channels (Balabanis et al., 2006; Balasubramanian, Raghunathan, & Mahajan, 2005; Black et al., 2002; Burnham et al., 2003; Gupta et al., 2004a; Maity & Dass, 2014; Muthitcharoen et al., 2011; Robertson, 2012). The proposed relations will thus build a profound basis for prospective research endeavors.

Fourthly, our research *reconstructed the cognitions of consumers that lead to rejection of m-commerce* by applying the means-end theory. This provides groundwork to explain consumer decisions from the outset of their formation, and enables an in-depth understanding of the psychological mechanisms that determine m-commerce adoption, as requested by several scholars (Hoehle et al., 2012). This structures the decision process hierarchically and prevents the confusion of different hierarchy levels (Pagani, 2004; Yang et al., 2015). As a result, prospective research approaches can better allocate their focus and select variables under the premise of structural clarity. This also applies to the classification of attributes by using variables from the ISSM, including service, system and information quality. The threefold division facilitates the prioritizing of future research by explaining the observed varying importance of these categories in past literature through referencing to the complexity of the product. The approach helps to unify the literature on barriers in m-commerce (Ram & Sheth, 1989) by reframing existing knowledge in an up-to-date setting. Our findings substantiate similar findings using the means-end approach (Kuisma et al., 2007) and those that scrutinize financial services such as mobile banking to explore resistance (Laukkanen et al., 2007).

Lastly, in this thesis we *augment knowledge about the handling of complex products in digital channels*. This enriches the broad majority of literature focusing on retail. Obviously, complex products are more complicated to investigate since they are abstract, manifold, intangible and hard to evaluate or, in other words, less "sexy" than simple goods (Devlin, 2007; Keh & Sun, 2008). Nevertheless, products such as insurance are inevitable and essential in life and deserve high prominence in research. Therefore, the presented insights are of considerable value and can pave the way to increase the number of investigations devoted to complex products in IS research. Our research confirms numerous findings which identified complex products as basis of switching barriers (Burnham et al., 2003), more need for information (Maity & Dass, 2014) and support (Ding et al., 2010; Ding et al., 2007) as well as increased perceived risks and uncertainty (Holak & Lehmann, 1990).

6.2.2 Practical Implications

In this thesis we addressed numerous practical issues concerning the implementation of m-commerce for complex products. As a central statement of this thesis, we highlighted the meaning of a service-task-technology fit. This indicates three areas of action for practitioners: Firstly, *insurance companies need to master complexity inherent to the task* (insurance purchase) as central source of resistance. In accordance with the barriers to m-commerce this can be achieved by providing complete, reliable and trustworthy information surrounding the product. Another option is to supply information iteratively regarding their level of detail, starting from superficial summaries to granular information to promote the product encounter at consumers' choice. This not only concerns the covered cases, but also the uncovered cases as well as pros and cons of the insurance policy to create a trustful relationship. Practitioners should further invest in a flexible channel design tailored to the consumers' characteristics. As inferred from the data, consumers differ in their processing style (i.e. due to different expertise), which in turn affects the purchase intention. Providers could thus cluster their consumers and automatically provide different kinds of information for different groups or allow people to decide by themselves which kind of information they wish to see. For instance, this could be accomplished by evaluating the characteristics and preferences when registering as a user of m-commerce, or by providing according information filters in the settings. As a last point, complexity can also be mastered by increasing the knowledge of m-commerce, for example by fostering trialability and observability of usage (Rogers, 1995). Insurance companies should thus invest in marketing campaigns to increase popularity of m-commerce and reduce stereotypes.

Secondly, *mobile insurance has to be improved in terms of service quality* as an appropriate means to counteracting complexity and associated factors such as risk. It was shown that there is a prevailing underinvestment of service in m-commerce. Companies therefore need to invest considerably in the opportunities of face-to-screen service in order to provide consumers with service features that meet their preferences and needs. Consequently, we proposed a comprehensive (hybrid) approach incorporating both TMS and TGS. For TMS, well-known service components include call, chat, email support and a location based agency finder. However, there are many under-utilized possibilities, which need to be evaluated (Hausman & Siekpe, 2009) such as audio and video chat, inter-consumer service or frequent broadcasts on online product presentations by experts. Moreover, our study outlined a higher fit for TGS with m-commerce supported by a higher efficiency in reducing risks. In turn, the utilization of TGS has to be augmented and can make use of features such as assurance, privacy, trust and test seals, video and audio product tutorials, info buttons, guarantees and third-party reviews. Many of these functions are well-established in other areas (e.g. in e-retail) and can easily be adapted to m-commerce. Nonetheless, due to synergies only a combination of TMS and TGS compensates the gaps of service in m-commerce. In contrast to retail, it can be noted that the insurance industry is not yet threatened by an overinvestment of service in m-commerce. However, to prevent experienced consumers from being distracted by redundant service, practitioners have to keep track of consumers' degree of adaption to m-commerce in order to consistently customize the amount of service.

Thirdly, *practitioners need to invest in the technological performance of m-commerce* in order to reduce resistance. Poor ergonomics was the main reason preventing consumers from using m-commerce. As pointed out by several scholars (Cao et al., 2014) this includes improvement of the processing speed and backend communication, the bandwidth and Wi-Fi coverage, as well as battery power and charging facilities. Furthermore, the process should be provided with intermediate storage, backups and possibilities to recover lost information immediately. Additionally, interviewees complained about handling effort. Therefore, mobile architects should enhance the user interface in terms of information amount, e.g. by reducing content through more visuals such as symbolic icons and animations; the structure of information, which can for instance be accomplished by wrapping content and providing links instead of details; and by optimizing the system response to consumer actions. Further related to the system quality of mobiles, many concerns involved the security of data and financial transactions. Practitioners should thus invest in their IT-security concepts. This includes a strongly encrypted server communication, multi-factor authentication for major changes, provision of diverse and established payment options such as Paypal and direct debit, and granting support in case of data abuse as, for instance, provided by the "Allianz DigitalSchutz", which covers any financial loss incurred during online transactions. However, consumers were also concerned about the treatment of personal data. Insurance companies should thus commit to reducing the data evaluation as a means to generate corporate profit. For instance, consumers were afraid of policies that discriminate against less active people. This prevents many people from giving insurance companies access to their mobile device (i.e. via apps) and needs to be questioned from an ethical and moral standpoint.

6.3 Limitations and Future Research

The present thesis has some limitations, which are discussed in the following. By considering insurance, we investigated a representative product of the family of financial services. This, however, holds two limitations: In Study 1 and 2 we generalized our results across different insurance products, while in Study 2 and 3 we referred to short-time insurance (e.g. travel insurance). Although all insurance policies share similar attributes, they can differ widely in terms of complexity. The found service relation therefore needs more elaboration for different products within insurance. We found similar results in other areas such as mobile banking and mobile ticketing (Laukkanen et al., 2007; Luo et al., 2010; Mallat et al., 2009) although our investigations excluded the retail market with goods. The relations should thus be challenged in other areas and for other products in the future.

A further limitation concerns the investigated time of product encounter. We considered the initial product contact, research phase and potential purchase of a non-established product. However, we did not systematically distinguish between different steps such as the gaining of knowledge, and phases of persuasion and decision-making (Rogers, 1995), nor did we consider post-purchase behavior. As previously mentioned, the observed moderations induce a continuous change (e.g. service need and risk decreases over time). It would therefore be of considerable value to perform long-term investigations in order to obtain better predictions for relational changes over time.

We obtained our data basis from field surveys and a laboratory experiment. Although this provides a solid basis, it might be biased compared to real-life data, as, for instance, stated for Study 3 the manipulation check between service and non-service condition revealed relatively small differences. Moreover, the exposition of participants to mock-ups of apps, leads to less cognitive penetration of the app compared to actual use. The found results may thus underestimate the effects that would occur in a real-life setting. This pitfall should be addressed in the future.

The described interview coding provides room for interpretation, which leads to deviations in the categorization of responses among raters. Although we approached this circumstance by basing our evaluation on the work of three coders, with a satisfying outcome, there were partly deviations in the length of chains that were extracted. This is not surprising, since m-commerce is a new and complex field. Future studies should stick to the multi-rater procedure and try to replicate these findings.

Lastly, our studies neglected the specification of service features and their impact on acceptance. Although the service types TMS and TGS were shown to be of considerable value, it is not clear which service functions are particularly important. This limits the findings in Study 4, where we attested a higher efficiency for TGS. The difference could, however, be a result of individual service functions. Future studies should therefore scrutinize the value of single features in order to provide concrete implications to counteract resistance. This can be augmented by differentiating the consuming groups. Female consumers, for example, often show higher risk perceptions in online purchases (Garbarino & Strahilevitz, 2004). In Study 4 we also found inconsistencies in purchase intention between age groups consistent to prior literature (Khare et al., 2012; Simon & Usunier, 2007). This leads to the assumption that different consumer characteristics cause different service needs. Therefore, demographical, as well as sociographical, aspects should be covered in more detail in future research on service.

6.4 Outlook

The goal of this thesis was to obtain a comprehensive understanding of the mechanisms that determine m-commerce resistance for complex products and to generate countermeasures that mitigate the prevailing adoption inertia. The conducted studies disclosed the sources of m-commerce resistance and have differentiated the view by demonstrating the influence of consumer characteristics on channel choice. Built on these insights, efficient means to master the adoption resistance were explored. The results highlighted the implementation of a comprehensive service as an appropriate tool to compensate the inherent complexity of mobile insurance. Although the merging of m-commerce and insurance remains a major challenge in upcoming years, it should still be achievable by applying the knowledge provided in this thesis. In conclusion, there is harmony between “new channels and old businesses”, it is just hidden behind the structures we have become accustomed to.

7 References

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8 Appendix

8.1 Appendix Study 1

Appendix 8.1 *Measurement Scales.*

Scale	Items	Adapted from
Complexity	1. The services of this insurance are difficult to understand. 2. An insurance agent selling this kind of insurance needs to know a lot. 3. This insurance is complicated in nature.	(Burnham et al., 2003)
Insurance Expertise	1. I consider myself experienced with regard to insurance. 2. I consider myself knowledgeable regarding insurance. 3. I know somewhat more than most others about insurance. 4. I am extremely skilled at insurance.	(Jaiswal et al., 2010)
Psychological Risk	1. When I purchase this insurance I would feel uneasy. 2. When I purchase this insurance it would give me a feeling of anxiety. 3. When I purchase this insurance it would cause me to experience unnecessary tension.	(Crespo et al., 2009; Featherman & Pavlou, 2003; Stone & Grønhaug, 1993)
Purchase Intention	1. Suppose you need to buy this insurance product in the next month, how probable is it that you would buy it via App? (anchored from very improbable to very probable) 2. Suppose you need to buy this insurance product in the next month, how willing would you be to buy this insurance via App? (anchored from very unwilling to very willing)	(Gupta, Su, & Walter, 2004b; Kozup et al., 2003)

Notes. The shown items reflect the retranslated version from German into English.

8.2 Appendix Study 2

Appendix 8.2 *Categories with Citation Examples.*

Code	Category	Example[a]
1	Limited Choice and Monopolism	• "So the broad offer just in one App, I don´t know, I believe that is difficult."
2	Poor Ergonomics	• "Well, Apps come along with such a small display and it requires zooming all in..."
3	Inferior Information Content	• "Because Apps are simple-minded (...), but cannot provide the range of information that is required."
4	No Personal / Individual Contact	• "Because I strongly value communication, also the non-verbal communication..."
5	Payment Concerns	• "…when changing to the app or the mobile channel it urges me to enter all my data once again."
6	Uncertain Data Handling	• "Because I just don´t know, if data can be intercepted…"
7	Image Discrepancy	• "Apps are more of a gadget for me. (...) That appeals dubious to me."
8	Technical Insufficiency	• "...it most likely performs jerking and also the waiting times, when switching a site"
9	No Service Advice & Support	• "...an insurance agent at least can give professional answers to some questions."
10	No Paper Proof	• "I would finally miss the printed form that I like to hold in the hand."
11	Lack of Documentation and Clarity	• "… when the debits get relevant (...) I need consciousness in this moment, what actually happens now."
12	Process Effort Takeover	• "I have the feeling that I need to perform the information research by my own."
13	Limited Scope of Action	• "So for me it feels as if my scope for action is taken"
14	Handling Effort and Mistakes	• "It promptly happens to push a button with the finger, which then causes the conclusion of a yearly contract and then you get stuck in it."
15	Insufficient Decision Basis	• "… that I would also fear, that a provider offers me less information, as he would do on other distribution channels (…] and therefore my information situation, hence my starting point, is worse right from the beginning."
16	Data Disclosure	• "...if it is sensible data, that he behaves mischievously with those, which harms me or brings unnecessary inconvenience."
17	Lack of Trust and Mistrust	• "I have a general mistrust regarding insurance, I believe."
18	Privacy Concerns	• "I don´t want have my personal data go round in the internet."
19	Financial Burden	• "That means, in the case of an incidence I may need to bear the costs by myself."
20	Choice Uncertainty	• "And if then an incidence occurs, I would not at all know, if this is covered..."
21	More Time Effort	• "This is an unnecessary time waste."
22	Convenience	• "Men always follow the line of the least resistance or try to follow this line, except the way of resistance promises so much, that it´s worth to go it."
23	Economy	• "I don´t want to pay a lot for little performance, that´s against the nature of humans."

Appendix 8.2 *Categories with Citation Examples. (Continued)*

Code	Category	Example[a]
24	Performance	• "Because it is the nature and purpose of an insurance to cover damages, which I cannot bear instantly and therefore I want to get the optimal product."
25	Privacy	• "That can of cause have financial consequences too, when an app notices that I am always mountain climbing and injure my ankle every half a year."
26	Compatibility	• "And I feel this is very important, because I am a tradition-conscious person..."
27	Material Security	• "It can lead to a threat for my financial existence."
28	Personal Security	• "That I (...) for a necessary operation can use it to safe my like."
29	Self-Determination	• "…this factor causes that my life could get significantly influenced. (…], this would provoke a feeling of absolute powerlessness."
30	Self-Actualization	• "I believe that time is the greatest good that humans have in today's stressful time. And with the reduction (...), I would win more time for other things."

Notes. [a] The citations mainly reflect word-by-word translations from German into English.

8.3 Appendix Study 3

Appendix 8.3 *Test Results of Internal Reliability and Convergent Validity.*

Construct	Items	Internal Reliability		Convergent Validity		
		Cronbach's α	Item-total correlation	Factor Loading	CR	AVE
Service Quality	4	.889	.785	.848	.885	.658
			.740	.828		
			.794	.829		
			.708	.734		
Information Quality	4	.885	.790	.874	.910	.720
			.782	.887		
			.743	.928		
			.682	.684		
Financial Risk	3	.779	.582	.877	.835	.633
			.619	.624		
			.647	.861		
Performance Risk	4	.900	.774	.806	.889	.669
			.758	.731		
			.781	.840		
			.796	.886		
Psychological Risk	3	.938	.890	.943	.938	.834
			.855	.895		
			.867	.901		
Time Risk	3	.874	.743	.820	.879	.710
			.713	.775		
			.823	.925		
Privacy Risk	3	.880	.778	.867	.881	.711
			.750	.806		
			.778	.856		
Insurance Expertise	4	.940	.847	.907	.933	.778
			.872	.936		
			.841	.826		
			.869	.856		
Smartphone Expertise	4	.934	.824	.907	.922	.750
			.876	.971		
			.830	.774		
			.849	.797		
Purchase Intention	2	.902	.821	.927	.902	.822
			.821	.886		

Appendix 8.4 *Measurement Scales.*

Scale	Items	Adapted from
Service Quality	1. When you have a problem, the service functions of the app provide possibilities to solve it. 2. The service functions of the app always provide opportunities to obtain help. 3. The service functions of the app provide the necessary knowledge to answer my questions. 4. The service functions of the app respond to my specific needs.	(Wang, 2008)
Information Quality	1. The app provides the precise information to the insurance that I need. 2. The information content to the insurance meets my needs. 3. I feel the output that the app provides, is reliable. 4. The app provides up-to-date information.	(Wang, 2008)
Performance Risk	1. I am concerned that the product will not provide the level of benefits it promises 2. There many possibilities that the product will not perform as it is supposed to. 3. The insurance product is extremely risky in terms of how it would perform. 4. The risk that this product will not perform as expected is high.	(Crespo et al., 2009; Featherman & Pavlou, 2003; Jarvenpaa & Todd, 1996; Stone & Grønhaug, 1993)
Financial Risk	1. I am concerned that I really would not get my money´s worth from the insurance. 2. There is a high chance that I will stand to lose money because an insurance case will not occur. 3. There is a high chance that I will stand to lose money because this insurance costs more than it should to maintain it.	
Time Risk	1. I feel concerns about wasting too much time making the purchase of this insurance. 2. There are many possibilities that I have to spend too much time searching for the right insurance composition. 3. The purchase of this insurance will lead to a loss of convenience for me because I would have to waste a lot of time.	
Psychological Risk	1. When I purchase this insurance I would feel uneasy. 2. When I purchase this insurance it would give me a feeling of anxiety. 3. When I purchase this insurance it would cause me to experience unnecessary tension.	
Privacy Risk	1. When I purchase this insurance there would be many chances that my personal information would be used without my knowledge. 2. When I purchase this insurance it would increase the possibilities that I would receive unwanted notifications (e.g. letters, messages, mails). 3. When I purchase this insurance it would lead to a loss of privacy because of the improper use of my personal information.	
Purchase Intention	1. Suppose you need to buy this insurance product in the next month, how probable is it that you would buy it via App? (anchored from very improbable to very probable) 2. Suppose you need to buy this insurance product in the next month, how willing would you be to buy this insurance via App? (anchored from very unwilling to very willing)	(Gupta et al., 2004b; Kozup et al., 2003)

Appendix 8.4 *Measurement Scales. (Continued)*

Scale	Items	Adapted from
Insurance Expertise	1. I consider myself experienced with regard to insurance. 2. I consider myself knowledgeable regarding insurance. 3. I know somewhat more than most others about insurance. 4. I am extremely skilled at insurance.	(Jaiswal et al., 2010)
Mobile Device Expertise	1. I consider myself experienced with regard to mobile Apps. 2. I consider myself knowledgeable regarding mobile Apps. 3. I know somewhat more than most others about mobile Apps. 4. I am extremely skilled at mobile Apps.	(Jaiswal et al., 2010)

Notes. The shown items reflect the retranslated version from German into English.

Appendix 8.5 *Comparison of Competing Models in the Structural Model.*

	χ2	Δχ2	Df	χ2/df	AGFI	SRMR	RMSEA	TLI	CFI	BIC	CAIC
Model 1[a]	3278.7**		448	7.32	0.68	0.208	0.091	0.75	0.81	4486	4668
Model 2[c]	2794.8**	483.9**	447	6.25	0.71	0.190	0.083	0.80	0.85	4009	4192
Model 3[c]	1686.6**	1108.2**	439	3.84	0.84	0.091	0.061	0.89	0.92	2954	3145
Model 4[d]	1193.8**	492.8**	436	2.74	0.87	0.041	0.048	0.93	0.95	2481	2675
Model 5[e]	1094.5**	99.3**	431	2.54	0.89	0.038	0.045	0.94	0.96	2415	2614
Model 6[f]	1098.8**	-4.3	436	2.52	0.89	0.038	0.045	0.94	0.96	2391	2586

Notes. N = 762; AGFI = Adjusted Goodness of Fit Index; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation; TLI = Tucker-Lewis Index, CFI = Comparative Fit Index; BIC = Bayesian Information Criterion; CAIC = Consistent Akaike Information Criterion. The postulated model was build up iteratively, following the iterations a to f.

a No relations between IV.

b Path between SQ and IQ added.

c Paths between SQ/IQ and Risks added.

d Paths setting performance risk as superior risk dimension predicting all other risks added.

e Path setting psychological risk as final risk dimension bundling all other risks.

f All paths that should disappear through mediation erased.

* p < .05., ** p < .01.

Appendix 8.6 *Hierarchical Polynomial Regression Results for all Risk Dimensions with Service Quality and Information Quality.*

	Step 2 Linear Effect					Step 3 Interaction Effect					Step 4 Quadratic Effect					Step 5 Cubic Effect				
	PerfR	FinR	TimeR	PrivR	PsyR	PerfR	FinR	TimeR	PrivR	PsyR	PerfR	FinR	TimeR	PrivR	PsyR	PerfR	FinR	TimeR	PrivR	PsyR
Step 2: Linear Effect																				
Risk	-0.33 **	-0.22 **	-0.22 **	-0.22 **	-0.41 **	-0.33 **	-0.22 **	-0.22 **	-0.22 **	-0.41 **	-0.33 **	-0.22 **	-0.22 **	-0.22 **	-0.41 **	-0.42 **	-0.28 **	-0.27 **	-0.23 **	-0.50 **
SQ	0.37 **	0.42 **	0.43 **	0.40 **	0.33 **	0.37 **	0.42 **	0.43 **	0.40 **	0.34 **	0.36 **	0.42 **	0.43 **	0.39 **	0.33 **	0.37 **	0.43 **	0.43 **	0.39 **	0.35 **
Risk	-0.29 **	-0.18 **	-0.18 **	-0.20 **	-0.36 **	-0.30 **	-0.18 **	-0.19 **	-0.20 **	-0.36 **	-0.29 **	-0.18 **	-0.18 **	-0.19 **	-0.36 **	-0.37 **	-0.24 **	-0.20 **	-0.20 **	-0.44 **
IQ	0.41 **	0.47 **	0.47 **	0.45 **	0.36 **	0.40 **	0.46 **	0.47 **	0.44 **	0.36 **	0.41 **	0.48 **	0.49 **	0.46 **	0.37 **	0.43 **	0.49 **	0.49 **	0.46 **	0.39 **
Step 3: Interaction Effect																				
Risk x SQ						-0.04	-0.03	0.00	-0.04	-0.03	-0.04	-0.03	0.00	-0.05	-0.03	0.00	0.00	0.03	-0.04	0.00
Risk x IQ						-0.04	**-0.05** *	-0.04	-0.03	**-0.06** *	-0.03	-0.04	-0.03	-0.02	**-0.06** *	0.01	-0.01	-0.02	-0.02	-0.01
Step 4: Quadratic Effect																				
SQ²											-0.01	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	-0.01	-0.01
IQ²											0.02	0.04	0.05	0.03	0.01	0.03	0.05	0.05	0.03	0.02
Step 5: Cubic Effect																				
Risk x SQ²																**0.06** **	**0.05** *	**0.05** *	0.01	**0.07** **
Risk x IQ²																**0.05** **	**0.05** *	0.01	0.01	**0.06** **
R^2(SQ)	0.41 **	0.35 **	0.35 **	0.35 **	0.46 **	0.41 **	0.35 **	0.35 **	0.36 **	0.46 **	0.41 **	0.35 **	0.35 **	0.35 **	0.46 **	0.42 **	0.36 **	0.35 **	0.35 **	0.47 **
R^2(IQ)	0.43 **	0.39 **	0.39 **	0.39 **	0.47 **	0.43 **	0.39 **	0.39 **	0.39 **	0.47 **	0.43 **	0.39 **	0.39 **	0.39 **	0.47 **	0.44 **	0.40 **	0.39 **	0.39 **	0.48 **

Notes. The presented results for Service Quality (SQ) and Information Quality (IQ) were calculated in two separate stepwise regressions. Step 1 "Control Effect" is not displayed in this table. Numbers in bold show significant interaction, quadratic and cubic effects.

8.4 Appendix Study 4

Appendix 8.7 *Measurement Scales.*

Scale	Items	Adapted from
Service Quality (SQ)	The insurance app… 1. …anticipates and responds promptly to user needs and request 2. …can be depended on to provide whatever is promised 3. …instills confidence in users, reducing their uncertainty 4. …understands and adapts to the user's specific needs 5. …gives a professional and competence image	(Ahn et al., 2007)
Information Quality (IQ)	1. Has sufficient contents where I expect to find information 2. Provides complete information 3. Provides accurate information 4. Provides timely information 5. Provides reliable information 6. Communicates information in an appropriate format	(Ahn et al., 2007)
Performance Risk	1. I am concerned that the product will not provide the level of benefits it promises 2. There many possibilities that the product will not perform as it is supposed to. 3. The insurance product is extremely risky in terms of how it would perform. 4. The risk that this product will not perform as expected is high.	(Crespo et al., 2009; Featherman & Pavlou, 2003; Jarvenpaa & Todd, 1996; Stone & Grønhaug, 1993)
Financial Risk	1. There is a high chance that I will stand to lose money because this insurance costs more than it should to maintain it 2. There is a high chance that I will stand to lose money because this insurance product will not be used 3. I am concerned that I really would not get my money´s worth from the product	
Time Risk	1. There are many possibilities that I have to spend too much time searching for the right insurance composition. 2. I feel concerns about wasting too much time making the purchase of this insurance. 3. The purchase of this insurance via app will lead to a loss of convenience for me because I would have to waste a lot of time.	
Psychological Risk	1. When I purchase this insurance I would feel uneasy. 2. When I purchase this insurance it would give me a feeling of anxiety. 3. When I purchase this insurance it would cause me to experience unnecessary tension.	
Perceived Ease of Use (PEOU)	1. Learning to apply this insurance app is easy for me 2. My interaction with this insurance app is clear and understandable 3. It is easy for me to become skillful at handling this insurance app 4. Using this insurance app requires a lot of mental effort. 5. I find it easy to get this insurance app to do what I want it to do 6. I find this insurance app user friendly	(Ahn et al., 2007)

Appendix 8.7 *Measurement Scales. (Continued)*

Scale	Items	Adapted from
Perceived Usefulness (PU)	1. Using this insurance app helps me to get better decisions 2. Using this app improves the efficiency of my conclusion of the insurance policy 3. Using this insurance app saves me money 4. Using this app increases my productivity of the conclusion of the insurance policy 5. Using this app improves my quality of the conclusion of the insurance policy	(Ahn et al., 2007)
Purchase Intention	1. Would you rather buy or not buy the insurance via app, given the information shown. 2. Given the information shown, how probable is it, that you would consider the purchase of the insurance via app? 3. How probable is it that you would purchase the insurance via app, given the information shown?	(Kozup et al., 2003)

Appendix 8.8 *Reliability, Validity and Model Fit.*

Construct	Items	Internal Reliability		Convergent Validity		
		Cronbach's α	Item-total correlation	Factor Loading	CR	AVE
Service Quality	5	.806	.599	.818	.900	.645
			.514	.676		
			.706	.873		
			.554	.739		
			.584	.889		
Information Quality	6	.842	.693	.905	.879	.553
			.618	.768		
			.584	.669		
			.558	.595		
			.687	.841		
			.631	.635		
Performance Risk	4	.908	.712	.742	.901	.695
			.833	.859		
			.829	.875		
			.804	.853		
Financial Risk	3	.724	.514	.562	.767	.529
			.538	.791		
			.588	.804		
Time Risk	3	.900	.755	.962	.908	.768
			.873	.797		
			.792	.862		
Psychological Risk	3	.924	.842	.902	.928	.813
			.901	.967		
			.796	.830		
Perceived Ease of Use	6	.886	.753	.759	.858	.503
			.787	.687		
			.679	.616		
			.624	.715		
			.710	.700		
			.681	.767		

Appendix 8.8 *Reliability, Validity and Model Fit. (Continued)*

Construct	Items	Internal Reliability		Convergent Validity		
		Cronbach's α	Item-total correlation	Factor Loading	CR	AVE
Perceived Usefulness	5	.848	.658	.768	.838	.515
			.694	.696		
			.506	.527		
			.706	.678		
			.735	.873		
Purchase Intention	3	.924	.850	.889	.925	.645
			.827	.865		
			.864	.935		
Fit: $\chi^2(602) = 910$, $\chi^2/df = 1.5$, AGFI = .75, RMSEA = .052, TLI = .92, CFI = .93						

Appendix 8.9 *Means of Service Types.*

	SQ	IQ	PerfR	FinR	TimeR	PsyR	PU	PEOU	PI
CG	4.23	4.91	4.38	3.68	2.22	4.27	4.10	6.02	3.77
TMS	4.52	4.89	4.73	4.20	2.05	4.82	4.16	6.04	3.60
TGS	4.77	5.05	4.48	3.67	2.41	4.13	4.22	5.91	3.92
CTS	4.93	5.36	4.13	3.80	2.05	3.64	4.22	6.40	4.12
Total	4.61	5.05	4.43	3.84	2.19	4.22	4.17	6.09	3.85

Notes. CG = Control Group, TMS = Technology-Mediated Service, TGS = Technology-Generated Service, CTS = Comprehensive Technological Service, SQ = Service Quality, IQ = Information Quality, PsyR = Psychological Risk, PerfR = Performance Risk, FinR = Financial Risk, TimeR = Time Risk, PEOU = Perceived Ease of Use, PU = Perceived Usefulness, PI = Purchase Intention.