International Journal of Electronic Commerce

ISSN: 1086-4415 (Print) 1557-9301 (Online) Journal homepage: http://www.tandfonline.com/loi/mjec20

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To cite this article: Jörg Heinze & Christian Matt (2018) Reducing the Service Deficit in M-Commerce: How Service-Technology Fit Can Support Digital Sales of Complex Products, International Journal of Electronic Commerce, 22:3, 386-418, DOI: 10.1080/10864415.2018.1462940

To link to this article: https://doi.org/10.1080/10864415.2018.1462940

Reducing the Service Deficit in M-Commerce: How Service-Technology Fit Can Support Digital Sales of Complex Products

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ABSTRACT: Mobile commerce still experiences high drop-out rates throughout the sales process. This is especially evident for complex products such as insurance, which consumers often initially explore online but complete the purchase offline to enjoy direct human assistance, helping them to better understand the product and reduce associated risks. To facilitate complex product purchases online, this article highlights the need for fit between the type of service and the type of technology used for the purchase, termed as service-technology fit (STF). In particular, the article proposes a comprehensive technological service (CTS); that is, the combination of a technology-mediated service (TMS) and a technology-generated service (TGS) as a central element of a face-to-screen service (FtoS). This experimental study found a significant superiority for CTS 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, relying solely on either TMS or TGS reduces the perceived service and information quality and reinforces the perception of several risks. These findings extend the theoretical knowledge on the mechanisms that are inherent to an FtoS service and give concrete practical implications for the future design of service in mobile commerce.

KEY WORDS AND PHRASES: Complex products, comprehensive technological service, mobile commerce, perceived risk, online risk, online service, technology-generated service, technology-mediated service.

Many companies use mobile commerce (m-commerce) to provide their customers with easy time- and location-independent access to their products. M-commerce helps companies to shift their usually expensive local service operations to the digital world, but m-commerce sales for complex products still lag behind since there is a high level of consumer resistance [52, 102]. Mobile insurance sales, for example, remain among the least attractive categories in m-commerce [97]. A key reason for this reluctance is the product-inherent complexity (i.e., when a product's characteristics and contractual details require significant effort to be fully understood to minimize associated risks) [12]. A comprehensive service that can help to mitigate these risks is therefore indispensable. It seems that m-commerce in general lacks sufficient integration of traditional offline or modern online service elements [40], which has led to a research online, purchase offline (ROPO)[1] principle for insurance consumers, implying that product research is done online but followed by a traditional offline purchase [54]. This stems from consumers' desire for self-determination and control during the purchase process [17].

International Journal of Electronic Commerce / Vol. 22, No. 3, pp. 386–418.

ISSN 1086–4415 (print) / ISSN 1557–9301 (online)
DOI: https://doi.org/10.1080/10864415.2018.1462940

The ROPO trend also highlights that there is a lack of service to support mobile insurance sales, and suggests that new approaches are required to satisfy consumers' needs for service in m-commerce.

Although the academic literature identified the particular characteristics and requirements of m-commerce at an early time [e.g., 39, 65], more than a decade later there remain substantial open questions on how to facilitate m-commerce in particular fields [90]. Potential ways of facilitating m-commerce sales for complex products are technology-mediated service (TMS) and technology-generated service (TGS) as introduced by Froehle and Roth [38]. A TMS represents a form of personal communication that is exclusively conducted via a technology-based medium; for instance, telephone, e-mail, or chat. It specifically involves human service, in contrast to a TGS, which is a fully automated service [37]. Both types are generally captured as a face-to-screen service (FtoS). Contemporary approaches toward selling complex products via m-commerce rely primarily on a TMS [51], which contradicts consumers' ROPO attitude as it neglects their need for self-controlled purchases due to the lack of self-service options. Further, sole reliance on a TMS fails to address the shortcomings in human-based service such as unethical behavior, poor employee skills, or temporal and spatial boundedness [42, 59, 69, 74]. By contrast, a TGS provides a range of advantages for consumers for online retail of simple goods; for example, using one-click ordering, trust seals, or integrated search engines [85]. Nevertheless, scholars have raised first concerns about the efficiency of a TGS or a TMS used separately [96]. In response, Selnes and Hansen [95] proposed a hybrid model that integrates self-service with personal service, implying a combination of a TMS with a TGS. However, whether a TMS or a TGS used individually is capable of facilitating m-commerce sales for complex products remains empirically unexplored, as does whether the combination of both, which we refer to as a comprehensive technological service (CTS), outperforms each of the two through synergies. We seek to reduce the existing research gap on the configuration of service in mobile channels and pose the following research question:

> ***Research Question:*** *How do different types of service affect the perceived fit and the purchase intention of m-commerce for complex products?*

To answer our research question we postulate that, for complex purchases, consumers' perceived fit of m-commerce is determined by the type of service that is provided to support them in performing the task. This assumption is based on the literature of fit and compatibility as, for instance, specified by the theorizing about cognitive fit [41] or resource matching [16]. To examine the perception of fit, we first evaluate the perceived service quality and the information quality before we assess established variables from the perceived risk-technology acceptance model [86]. The latter captures different risk facets together with perceived usefulness and ease of use, and has proven its predictive value regarding the purchase of complex products.

Our results extend the recent literature by providing new insights on the role of human and technological Web assistance in m-commerce. This leads to four major contributions for research: (1) We extend the concept of service as a key variable of fit to increase the purchase intention. (2) We clarify the impact of human service in the form of a TMS on purchase intention in m-commerce in contrast to a TGS. This allows for a better understanding of specific advantages and disadvantages of each service approach. (3) We elaborate on the knowledge about psychological mechanisms, which determine the purchase intention of complex products in m-commerce, especially regarding the association of services with perceived risks. (4) We provide insights into the service perception in the first moments of a consumer's interaction with a product presentation in m-commerce prior to a first personal contact. For practitioners, this leads to a better understanding of consumer interactions in m-commerce and reveals valuable implications for the design of mobile apps for complex products.

The remainder of this article is organized as follows. First, we provide an overview of the theoretical background and state our research hypotheses. Next, we present our experimental design and report the results. Finally, we discuss theoretical and managerial implications and suggest opportunities for future research.

Theoretical Background

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-understood. Nevertheless, virtual interaction has taken the world by storm and requires an updating of research to understand its effects on consumers' satisfaction. Mobile service is provided via screen and contains either personal Web assistance (~TMS), plain technological Web assistance (~TGS), or a combination of both [37], which we refer to as a comprehensive technological service (CTS). A TMS mainly consists of a human-based service via phone, chat, e-mail, or voicemail. To function well, a TMS depends heavily on the knowledge, skills, and abilities as well the individual traits of its human entity. These factors strongly affect the service's effectiveness and its perceived quality and can lead to either positive or negative outcomes. On the one hand, a TMS enables a quick, reliable, and competent processing of queries and, in addition to positive effects on consumers' loyalty and satisfaction, it also has a positive impact on feelings of perceived control and commitment toward a relationship [32, 44]. Service employees can often easily understand consumer requests, provide them with advice, and communicate in an appropriate manner to demonstrate empathy [80, 96]. This finally leads to a flexible and personalized interaction, and assists consumers in making a decision. Many providers have thus identified the potential of a TMS [44]. 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 [25]. This can lead to frustration, uncertainty, and mistrust, and is even more problematic for a TMS than for classical physical services owing to missing contextual information from in-store encounters [14].

In contrast, the reliance on a TGS (i.e., purely electronic service) has become increasingly common; for instance, by the implementation of digital service features such as frequently asked questions (FAQs), search functions, and information buttons [22]. These features place a strong emphasis on consumer self-service and reduce the need for interaction with a service employee [21]. Shopping on Amazon, for example, illustrates how such self-service technologies (SSTs) are applied. SSTs are technologies that are performed without any interaction or association with employees of the service provider [21, 74]. From a corporate perspective, this provides several benefits such as the standardization of service delivery, expanded options for delivery, reduced labor costs [21, 22, 25], differentiation through digital interaction [71], and the creation of a common understanding. However, concerns arise from technological failures, process failures, poor design, and consumer-driven failure (e.g., forgotten passwords) [22, 73, 74], which can be fatal due to low switching costs owing to minimized personal bonds [71, 95]. A 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 satisfaction [8, 22]. Consumers obtain more control over their product selection processes; for example, by customizing the product, which enhances convenience and enjoyment while using the technology [25]. Nonetheless, there are also concerns such as the lack of tailor-made advice that can only be offered by staff members [96]. Consumers are also required to spend an increased amount of time and make a greater cognitive effort to understand the technology as well as the product, without there being a staff member on hand to explain any complex issues [71, 96].

Service Assessment and Service-Technology Fit

In the literature on the success of information systems, three factors are seen as crucial: service quality, information quality, and system quality [28]. We base our theoretical frame on the former two nonengineering dimensions (i.e. service and information quality) and use these to quantify the change in the service assessment induced by a different type of service.

Service quality 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 [104]. Zeithaml, Parasuraman, and Berry [104] proposed five relevant dimensions for the assessment of service quality: reliability, responsiveness, empathy, assurance, and tangibles. Further subcategories were later added [5], which we present in online Appendix 2, together with the definitions 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. Among others, this includes the accuracy, timeliness, completeness, information reliability, and relevance of content in the m-commerce environment [29, 70, 83]. Information quality constructs revealed a good fit for e-commerce sites, and appear adequate for m-commerce [1].

Consumers' quality assessment of service results from the comparison of expected and provided service [84, 87]. The establishment of online shopping using different technologies has led to specific consumer expectations for the design of service for each channel. Based on cognitive fit assumptions, a higher congruence of service expectations and actual provision of service increases the speed and task accuracy and reduces cognitive load [41]. However, it remains unclear, how service expectations vary in relation to the technology that is used. Although certain types of services may facilitate the execution of a task when using one technology (i.e., e-commerce), the same services may inhibit the performance when switching to another technology (i.e., m-commerce). We refer to this phenomenon as *service-technology fit* (STF), which defines the ability of service to facilitate the execution of a task given that the service characteristics match the nature of the technology. Reasons for an increase can be found in cognitive fit theories such as the resource-matching theory. In essence, it claims that humans have limited resources (e.g., time, space, cognitive) in managing and accomplishing a task [2]. Consumers prefer the technology or channel that best suits their available resources (i.e., at the time, speed, and location of their own choosing), with convenient cognitive effort [106]. A service that is perceived suitable to the technological environment facilitates the cognitive processing through less effort of transforming the existing cognitive processes into the required cognitive processes to accomplish the task. This helps to reduce complexity and enables faster decision making with positive effects on the adoption of SSTs [16, 41].

While higher levels of fit support the acceptance of m-commerce in terms of purchase intention (PI), several other variables have been found to reflect the manifestations of fit between service and technology. Gefen and Pavlou [40, p. 941] stated that a high STF enhances buyers' belief "that appropriate conditions are in place to facilitate transactions with sellers" and thereby mitigates the role of perceived risks in the transaction process. In the context of m-commerce, *perceived risks* can be defined as the uncertainty about potential negative consequences or loss in the pursuit of a desired outcome using a mobile service and the value ascribed to this consequence or loss [18, 20]. A meta-analysis by Zhang, Zhu, and Liu [105] 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 [67] and can be divided into four subdimensions: performance, time, financial, and psychological risk [19, 35].

Pavlou [86] integrated perceived risk together with perceived usefulness (PU) and perceived ease of use (PEOU) in one spanning model to better describe the uncertain environment of e-commerce. According to Ahn, Ryu, and Han [1], service and information quality also have a beneficial effect on PU and PEOU. Further, PU, PEOU, and perceived risks all have been frequently applied to various mobile contexts [77, 105]. We therefore follow this path and simultaneously consider perceived risk, PU, and PEOU to comprehensively evaluate the influence of the different types of service in a complex purchasing environment.

Research Model and Hypotheses Development

A central goal of our research is to help increase the purchase intention for complex products in m-commerce by exploring users' initial service assessment (measured by service and information quality), and how they perceive STF, indicated by perceived risk, PU, and PEOU. We therefore altered the type of service through external service cues, all applied in an m-commerce setting with complex products (insurance), and measured consumers' final decision through their purchase intention (Figure 1). In the following, we derive our hypotheses.

Type of Service and Service Quality

When evaluating the service quality of a TMS, common practices of sales staff working for commission should be taken into account. Conflicts of interest and unethical behavior (e.g., withholding information) by the salesperson may occur. Consumers therefore often doubt the honesty and trustworthiness of salespeople [99], feel vulnerable [40], and have evolved stereotypes [36]. Transferred to m-commerce, the commission-driven sales

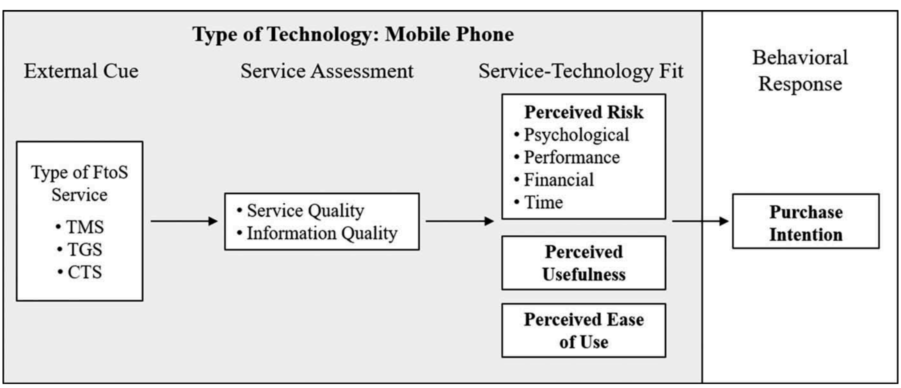


Figure 1. Conceptual Model.

Notes: FtoS = face-to-screen; TMS = technology-mediated service; TGS = technology-generated service; CTS = comprehensive technological service.

process might negatively affect consumers' perceptions of reliability, competence, credibility, and security for a TMS compared to a TGS.

Based on common online shopping principles, a technology-based distribution channel (e.g., m-commerce) is more compatible with technology-based service approaches due to a coherent media environment. For example, calling up a semitransparent overlay with page instructions in m-commerce should be preferred to a conventional call-an-agent function due to higher suitability of this feature with other technology-driven features in m-commerce. Moreover, the "anytime, anywhere" culture provided through mobile devices [9] is not fully compatible with the limited accessibility and responsiveness of service staff. This leads to lower resource-matching perceptions for a TMS. Collier and Kimes [16, p. 40] argued that "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." Moreover, a TGS enables easier public control; for example, through independent tests and user reviews that give consumers higher confidence in the reliability of information. Finally, coming from the social distance literature, a TMS requires consumers to overcome affective and interactive barriers in initiating a contact that is socially distant. Dickson and MacLachlan [31] argued that people shop less frequently in stores that have a great social distance from themselves. Similarly, Meuter, Ostrom, Roundtree, and Bitner [74] found that some people tend to use an SST to avoid contact with sales staff. In light of the ambiguous reputation of these commission-driven staff, and the fact that complex financial products can be assumed to be infrequently purchased [30, 60], social distance might inhibit the willingness to use a TMS. Social distance, however, plays no role for a TGS. To summarize, a TMS, rather than a TGS, is likely to create a poor service quality. In comparison, a CTS integrates the advantages of both alternatives and gives users the choice to use either TGS or TMS elements, and thus fulfills individual preferences more accurately. We thus hold:

> ***Hypothesis 1:*** The service quality is lowest for a TMS and increases for a TGS and a CTS with the highest values for a CTS.

Type of Service and Information Quality

Concerning information quality, both a TMS and a TGS have benefits and drawbacks. A TMS requires employee involvement in real time, and can thus help to answer complex nonstandard queries immediately as well as give reassurance regarding uncertainties [95]. Therefore, a TMS is able to transmit considerable levels 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. In addition, the effort of obtaining information, hampered by the process of contact initiation paired with limited operating hours, may be detrimental to the service convenience [7] and therefore negatively impact the information quality perception.

A TGS reveals a better fit of information format and channel attributes, which might increase the perceived appropriateness. This involves the aforementioned anytime, anywhere accessibility of information [16]. Furthermore, information can be thoroughly prepared by the provider, in terms of, for example, 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 a TGS carries the risk of being difficult to understand, outdated, and partly irrelevant [48], which may increase search and processing costs. Yet assuming decent editorial performance behind a TGS, it has the potential to reveal more tangible and suitable information for m-commerce, which increases the perception of information quality. Nevertheless, consumers' behavior in buying complex products often relies on multiple sources of information to reduce uncertainty as introduced by the ROPO principle [54]. Providing m-commerce users with relevant self-service information through a TGS, complemented with a personal contact for more demanding tasks through a TMS, is expected to attain the highest information quality by addressing the drawbacks of both services [95]. We pose the following hypothesis:

> ***Hypothesis 2:*** The information quality is lowest for a TMS and increases for a TGS and a CTS with the highest values for a CTS.

Service-Technology Fit and Risk Perception

In general, we assume that different types of service diverge in how they influence the perception of risk and its subdimensions. The following sections explain the related hypotheses in more detail.

Performance Risk

Consumers investigating complex products are prone to overseeing details, which can lead to wrong product choices and malfunctioning [23]. As noted, a core issue for a TMS is the widespread commission-driven sales process, which causes consumers to doubt the objectivity of the provided information [36, 55]. For example, service employees can easily manipulate decisions by withholding information. Without having other information sources available (e.g., a TGS), it is likely that consumers will lack confidence in the performance of the product. Performance risk further depends on the level of service and information quality [45, 78]. Following this argumentation, a TGS acts as a prerequisite for obtaining valuable information and can further be complemented by a TMS as a second instance to verify and fine-tune gathered information [80, 96].

Combining both thus diminishes their inherent deficits, with a particular need for a TGS in m-commerce. A CTS gives consumers time for exploration to acquire a detailed product knowledge before relying on human service, thus also lowering feelings of being pushed to buy a product [16]. Finally, this leads to the following hypothesis:

> ***Hypothesis 3:*** The performance risk is highest for a TMS and decreases for a TGS and a CTS with the lowest values for a CTS.

Financial Risk

A TMS is sometimes associated with unethical behavior such as pressuring consumers toward products or providing misleading information [91]. This is reinforced by the risk of the product not functioning in the expected way [59], which can lead to unexpected costs. Additionally, human-based services such as a TMS have generally been shown to be more costly than most kinds of SST, including a TGS [74, 95]. Despite lower cost estimations for a TGS, it runs the risk of there being more misunderstandings with consumers as well as system failures such as cancellations of the transaction or loss of private data [33]. This might increase the financial risk for a TGS in certain cases. Nevertheless, as we assume consumers to have a stronger perception of the higher financial costs for the product acquisition with a TMS, a TMS is assumed to evoke higher estimations of financial risk and thus less STF. Since a CTS incorporates the human component of service, we expect a moderate financial risk for a CTS. The following hypothesis is postulated:

> ***Hypothesis 4:*** The financial risk is lowest for a TGS and increases for a CTS and TMS with the highest values for a TMS.

Time Risk

While many scholars argue that time savings are the primary motivation to use SSTs [6], a diverging pattern can be observed for complex products that are only occasionally bought via new channels. This is due to the large amount of information that often needs to be considered [23, 67]. Therefore, the more service and information cues are presented, the more search effort needs to be conducted. On this subject, Simon and Usunier [96] argued that SSTs reveal more difficulties with interface handling and cannot duplicate all features of a face-to-face communication. For occasional purchases, such as insurance, this implies that a product encounter in the TGS condition (which the customer initiates independently without being prompted by a sales call) is deemed to be more time consuming than a personal consultation (or the delegation of the purchase to an agent) in a

TMS or CTS situation. Because a CTS comes as partial self-service, an intermediate time risk can be assumed. We thus hold:

> ***Hypothesis 5:*** The time risk is lowest for a TMS and increases for a CTS and TGS with the highest values for a TGS.

Psychological Risk

When using a TMS, consumers may experience a loss of control related to the process or the outcome of an interaction [17]. Recent studies emphasize the essential role of control as a driver of an SST [6, 32, 74] as well as a preventer of risks [45]. Applied to insurance, existing concerns about the unethical behavior of sales staff may cause feelings of low situational influence, along with situational discomfort. Together with the aforementioned concerns about social distance, this drives feelings of psychological risk in a TMS. The expected higher financial risk and performance risk further intensify the psychological risk [59].

In contrast, a TGS enables a flexible and self-controlled product encounter, usually without pressuring the consumer and with sufficient leeway for exploration [16]. It relieves consumers from contacting a salesperson [74] and simultaneously opens up free staff resources to address more difficult customer concerns [95]. Accordingly, it can be expected that a TGS increases the resource matching [16] and thus leads to higher convenience. A TGS can further serve to document the information exchanges between company and customer. Nonetheless, the high need for cognition can conversely intensify psychological risk for a TGS, but we assume this effect to be less striking compared to a TMS. Finally, the integration of both services combines their advantages and reduces their shortcomings. To conclude, we pose the following hypothesis:

> ***Hypothesis 6:*** The psychological risk is highest for a TMS and decreases for a TGS and a CTS with the lowest values for a CTS.

Service-Technology Fit and Purchase Intention

Several studies have demonstrated a positive effect of service and information quality on PEOU and PU [1, 11]. Following our previous theorizing, both a CTS and a TGS should be most likely to amplify PEOU and PU. Reasons are the extensive information that is provided, together with a comparably high service quality [67]. This enables an efficient decision and enhances the technological usefulness. The high service quality is also characterized by high aesthetics of the interface, together with easy navigation, which generates a high PEOU. High information quality enhances the transparency of the process and reduces risks [78], 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 [1]. This enhances its own performance by increasing decision speed and quality, and enables cost savings, leading to more PU [11]. Together with the enhancement of service and information quality as well as decreasing risks, we expect a substantial increase of PU and PEOU and, as a consequence, a higher intention to purchase [57, 86]. As noted, a CTS best matches the common ROPO principle and it offers the highest variety of service options to consumers. This leads to the following hypotheses:

> ***Hypothesis 7:*** The PU is lowest for a TMS and increases for a TGS and a CTS with the highest values for a CTS.

> ***Hypothesis 8:*** The PEOU is lowest for a TMS and increases for a TGS and a CTS with the highest values for a CTS.

> ***Hypothesis 9:*** The PI is lowest for a TMS and increases for a TGS and a CTS with the highest values for a CTS.

Research Methodology

Data Collection Procedures

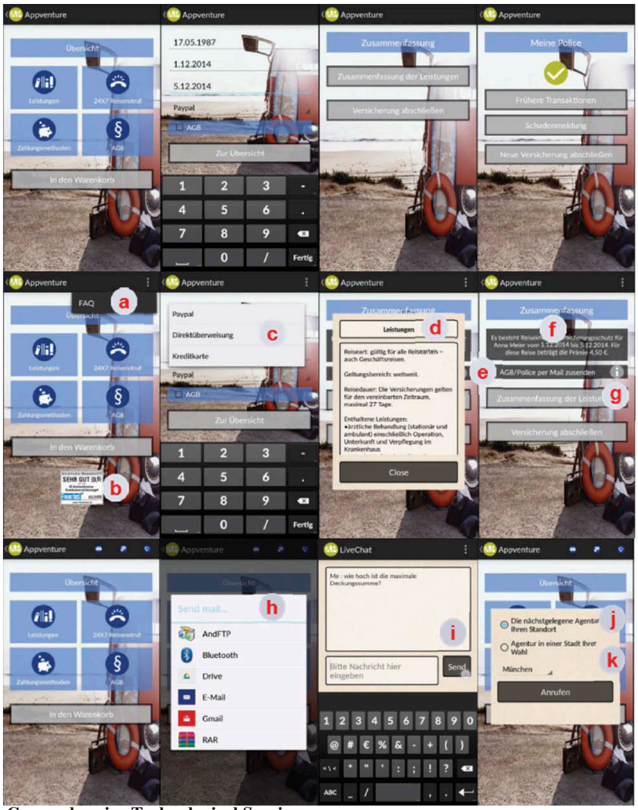
The hypotheses were examined in a laboratory experiment to have high control over the technology usage assignment and mitigate confounding interferences. For the study, we developed a specifically programmed app, which we altered slightly for each of four diverging conditions regarding the type of service that was provided. The fix part of the app consisted of a selection of four short-term insurance offers (insurance on a daily basis such as a travel insurance) presented on the first page. General information about the previously chosen product (service portfolio, payment, terms and conditions) was presented on a second page. The third page offered a form to enter personal data and select payment options, 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 provided 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. As part of this, the main features of the app were introduced visually, accompanied by an auditory explanation. 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 approximately 30 minutes. Two questions were included at the end to verify 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 answered Question 1 correctly and 98.9 percent answered Question 2 correctly. Therefore, a sufficient amount of attention to the experimental conditions was assumed for all respondents.

The four experimental conditions consisted of (1) a control group (CG), (2) a TMS, (3) a TGS, and (4) a CTS, embedded in the aforementioned sales environment. To find out which technological service features are favored for the operationalization of TGS, we had previously set up a focus group discussion using the guidelines of Kitzinger [62] and Mayerhofer [68]. The focus group was 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 were prioritized: (1) a summary of the insurance portfolio at the beginning; (2) the implementation of information buttons, (3) the implementation of frequently asked questions; (4) the implementation of a quality assurance seal; (5) the provision of different payment options; (6) an overview of the chosen product specifics before buying; and (7) the mailing of the policy and terms and conditions after the contractual conclusion. Figure 2 displays and summarizes all implemented features for each experimental condition.

Human service in e-commerce is seen as being an opportunity to access personal service via different channels; for instance, the availability of an agent's telephone number or e-mail address [13, 47]. Froehle [37] posited that telephone calls are among the most frequent means of consumer service communication. He also showed that e-mail and instant messaging (aka chat) belong to the preferred methods of consumer encounters. Consequently, we selected the following functions to operationalize TMS: (1) a contact option to call a local agent; (2) a contact option to call an agent at a preferred place (e.g., hometown); (3) an e-mail option; and (4) a live chat option. Finally, the CTS condition incorporated all the aforementioned features of a TMS and a TGS in one app. We also implemented a control group with no service features except the basic app design and functionalities.

Sample

We assigned all participants randomly to one of the four conditions and rewarded them with eight euros each. We chose a student sample as the relevant target group for service-based m-commerce since students are likely to be familiar with mobile devices as well as familiar with the Internet as a medium for communication and commercial transactions [23]. There were 188 participants who took part in the experiment, with an average age of 24.3 years (*SD* = 6.8; *MD* = 23.00) and a distribution of 108 women and 80 men. 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. This procedure indicates outliers, but should be followed by a logical and individual assessment of each case [81]. We therefore skimmed all those cases by hand for conspicuous patterns.



Control Group
No additional service features implemented

Technology-Generated Service
a. frequently asked questions
b. quality assurance seal
c. choice of payment options
d. insurance portfolio summary
e. mailing of policy, terms & conditions after conclusion
f. overview over the chosen product options before buying
g. information buttons

Technology-Mediated Service
h. e-mail option
i. live chat option
j. contact option to call an agent in the locational proximity
k. contact option to call an agent at a preferred place (e.g. home town)

Comprehensive Technological Service
Combination of all features implemented in TMS and TGS

Main menu items included in all conditions: overview, benefits, 24x7 travel emergency, payment options, terms and conditions, add to shopping cart

Figure 2. Screenshots of the Experimental Design with Implemented Features for Each Condition.

We dropped three cases due to an abnormal response behavior (e.g., one value for all items), but kept all other outliers so as not to exclude extreme opinions. Moreover, we excluded all respondents with an age that was more than three standard deviations beyond the group mean (~ extreme values) since multiple studies have shown that older people (50 years old or older) are more reluctant to use new technologies [27, 72, 96]. 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 [22, 27, 76]. We dropped five more cases. The final sample consisted of 180 participants (Table 1) with an average age of 23.47 years (*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.[2]

Table 1. 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
Mean	22.8	23.2	24.2	23.2	23.4
Education					
High school	34	32	34	33	133
Graduates (B.S. or M.S.)	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.

Measurement Development and Validation

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 Likert-type scale ranging from 1 (*strongly disagree*") to 7 (*strongly agree*). The items were translated into German following the process of item-equivalence [10]. This means, a bilingual person translated all items from English into German while a second bilingual person translated them backwards. Differences concerning the wording were discussed and solved by the translators and the authors.

To measure the constructs of service quality and information quality, we adapted scales from Ahn, Ryu, and Han [1]. PU and PEOU were examined by adjusting common items widely established in the literature [1]. Perceived risk was assessed by adapting scales, originating from Stone and Grønhaug [98], Jarvenpaa and Todd [53], and Featherman and Pavlou [33], and used by Crespo, del Bosque, and de los Salmones Sánchez [19]. Finally, for purchase intention, we adjusted a scale developed by Kozup, Creyer, and Burton [64] to our context. A first pretest with 10 professionals from the insurance business was conducted in advance to guarantee a clear understanding of all items and the instruction video. After fixing some remaining issues, we carried out a second pretest with 10 respondents consisting of students and researchers, which led to a comprehensible version of the experiment. An overview of all items is presented in online Appendix 3.

Since we adapted the constructs to the mobile context, we tested their internal reliability and convergent and discriminant validity next to whether the data fulfilled the assumptions of normal distribution and variance homogeneity.

First, to test the reliability, we calculated Cronbach's alpha and the item-to-total correlations. All alpha values ranged between .72 and .92 and thus exceeded the recommended threshold of .70. All items surpassed the commonly used threshold of .30 for the item-to-total correlation [79] with a range of .51 to .90.

Second, convergent validity was investigated by calculating the average variance extracted (AVE), composite reliability (CR), and factor loadings of the items. For these tests, values beyond .50 for the AVE and .60 for the CR are recommended [3, 34]. In accordance, all AVE values of the variables surpassed the threshold 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 common guidelines [49] 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 all 43 items, 27 had excellent factor loadings ($\beta > .71$), 8 items had good loadings ($\beta > .60$), and 3 items had fair loadings with a value above .50. The remaining 5 items were dropped from the analysis, leaving 38 items for the final analysis.

Third, 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. Finally, a confirmatory factor analysis was performed to assess the goodness of fit in a structural equation model by using the procedures as recommended for samples with less than 250 participants and more than 30 indicator variables [49]. Those are values smaller than 3 for the χ^2/df-ratio, values above .92 for the Comparative Fit Index (CFI), and values below .08 for the Root Mean Square Error of Approximation (RMSEA). In total, the model revealed an acceptable model fit: $\chi^2(602) = 910$, $\chi^2/df = 1.5$, CFI = .93, RMSEA = .052. It is important to note that larger sample sizes are likely to obtain more robust estimations [49, 81]. For the evaluation, 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 also controlled for missing data. In total, there were four missing values in the dataset. Due to this negligible amount (below 0.0003 percent out of all values) and their random distribution, we applied a simple mean substitution to utilize all gathered information. We conducted the analyses with IBM AMOS 22. Finally, the robustness of our measures obtained evidence through confirmed internal consistency and convergent and discriminant validity as well as a satisfactory model fit as shown in Table 2.

The results further revealed a violation of the normal distribution. Nevertheless, the values for skewness and for kurtosis were below

Table 2. Reliability, Validity, and Model Fit.

Construct	Items	Internal reliability		Convergent validity		
		Cronbach's α	Item-to-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		
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		

Notes: Fit: $\chi^2(602) = 910$, $\chi^2/df = 1.5$, AGFI = .75, RMSEA = .052, TLI = .92, CFI = .93. CR = control group; AVE = average variance extracted.

recommended thresholds of 3 and 10, respectively [63]. The collinearity was tested by calculating the variance inflation factor for all independent variables. All values were below 3.1 and thus did not exceed the recommended threshold of 5.0 [49]. Taken together, the data and the employed constructs appear to be valid for further analyses.

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 the recommendations of Podsakoff, MacKenzie, Lee, and Podsakoff [88] 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 is widely used to control for a severe CMB [66, 88]. Harman's single-factor test constitutes that CMB is prevalent when more than 50 percent of the covariance among all items can be explained by one common factor. Applied to our data, one factor explained 29.93 percent 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 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 toward insurance. All three measures had the same Likert-scale format. The outcome revealed a common variance of 3.24 percent over all items. Thus, CMB does not appear to be a serious threat for the interpretation of our data.

Manipulation Check

To verify that our manipulation was successful, showing a notable difference in the perception of technology-mediated and -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 such as electronic summaries and payment options?" For Question 1, a *t*-test showed that the TMS condition (M = 4.59) revealed a significantly 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 2, participants in the TGS condition perceived significantly better technological service than service through personal counseling (compared to Question 1, ΔM = 1.67, $t_{(46)}$ = 6.56, p < .01, d = 1.22) while in the TMS condition perceptions were more similar (ΔM = .73, $t_{(45)}$ = 3.67, p < .01, d = .52). However, the TGS and TMS did not differ significantly for the second question ($\Delta M_{\text{TMS-TGS}}$ = .39, $t_{(91)}$ = 1.40, p = .17). This might be due to some interpretation leeway; for example, participants might have confused general features in the TMS condition with technology-based functions. Nevertheless, the strong difference in the TGS between human-based and technological-based service supported an effective influence of our manipulation. Finally, a CTS should have values similar to a TMS for the first question and values equal to a TGS for the second question. Both assumptions were supported by insignificant differences ($\Delta M_{\text{TMS-CTS}} = -.13$, $t_{(87)} = .44$, $p = .66$; $\Delta M_{\text{TGS-CTS}} = -.51$, $t_{(88)} = -1.99$, $p = .05$). Overall, the manipulation appeared to be effective.

Results

To validate our hypotheses, we calculated multiple trend tests by using orthogonal contrast analyses. Compared to ANOVA, trend tests provide the advantage of not only testing the treatment differences between bilateral variables for significance, but also testing for the explicit order of several variables. Several scholars strongly recommend the use of contrasts whenever researchers have specific hypotheses that can be arranged in terms of expected mean differences between groups [15, 56, 92]. The main advantages of using contrasts compared to ANOVAs are higher power, effect sizes that are easier to interpret, the substitution of additional post hoc tests, and multiple means that can be compared at once. To code the contrasts, lambda-weights that sum up to zero were assigned according to the a priori defined hypotheses. For H1 and H2, this leads to the contrast weights of TGS 1, CTS 2, and TMS −3, indicating a superiority of the second. A summary of the means of all constructs for each condition and an illustration of all trends are shown in Table 3 and Figure 3.

As hypothesized, the treatments with a TGS or a CTS revealed a significant higher service quality compared to a TMS, with the highest value for the CTS ($F_{(1,176)} = 3.76$, $p < .05$, $\eta^2 = .021$). Thus, 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 the CTS. Thus, the results supported H2.

In H3, we stated the superiority of a 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

Table 3. 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; PerfR = performance risk; FinR = financial risk; TimeR = time risk; PsyR = psychological risk; PU = perceived usefulness; PEOU = perceived ease of use; PI = purchase intention.

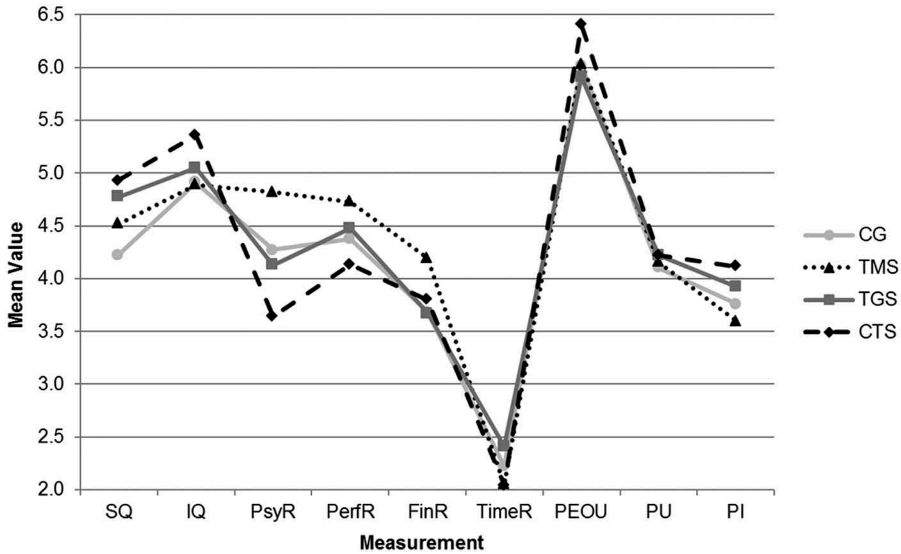


Figure 3. Mean Values of the Different Service Types.

Notes: 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.

of risk, lower contrast weights represent less risk perceptions. The predefined trend was significant with a small effect size ($F_{(1,176)} = 3.51$, $p < .05$, $\eta^2 = .020$). Thus, H3 was supported. In H4, we assumed a TMS to generate the highest perceptions of financial risk and decreasing values for a CTS and a TGS, with the 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 effect size. Conclusively, H4 was supported. For H5 involving time risk, we postulated a superiority of the TMS and an increase for the CTS and TGS with the highest risk value for the TGS (contrast weights: TMS –2, CTS –1, TGS 3). The overall trend revealed a significant result ($F_{(1,176)} = 3.72$, $p < .05$, $\eta^2 = .021$). In conclusion, H5 was supported by the data. H6 postulated that a TMS causes the highest perceptions of psychological risks while a CTS causes the lowest values (contrast weights: TMS 3, TGS –1, CTS –2). The data analysis provided support for this assumption ($F_{(1,176)} = 11.95$, $p < .01$, $\eta^2 = .064$) with a medium effect size. In turn, H6 was supported.

We next tested the superiority of the CTS for PU and PEOU as hypothesized in H7 and H8. Contrary to our hypotheses, the effects for PU ($F_{(1,176)} = .15$, $p = .70$) 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 the CTS over both variables. For PU, no significant difference between

Table 4. Summary of Hypotheses.

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
H9	Purchase intention	−3 1 2 [a]	Not supported

Notes: [a] Contrast coefficients in the order TMS, TGS, and CTS. TMS = technology-mediated service; TGS = technology-generated service; CTS = comprehensive technological service.

CTS and the remaining groups was found ($F_{(1,176)}$ = .03, p = .86), but the CTS revealed a significant higher PEOU in relation to all other conditions ($F_{(1,176)}$ = 10.303, p < .01, η^2 = .055).

Finally, we postulated a positive impact of a CTS on the intention to purchase a mobile insurance. The results did not reveal a coherent support for this assumption. Although CTS (M = 4.12) was the only value above 4,[3] and considerably exceeded the TMS condition ($\Delta M_{CTS\text{-}TMS}$ = .52; $F_{(1,176)}$ = 2.04, p = .16) and the CG ($\Delta M_{CTS\text{-}CG}$ = 0.35, $F_{(1,176)}$ = .93, p = .34), the effects were not significant. The postulated trend in H9 could not be confirmed ($F_{(1,176)}$ = 2.04, p = .16). A summary of the hypotheses tests is shown in Table 4.

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 [40]. With regard to insurance, the experience level of consumers grows in strong relation to different life phases. Therefore, young people who are just beginning to make their first independent decisions usually have less 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, η^2 = .054), when splitting the sample into two groups by the age of 21 years (18 to 21, n = 72 vs. 22 and older, n = 108). Even a subsequent exclusion of the cohort of 18- to 19-year-old respondents (n = 22) turned H9 into significance ($F_{(3,\ 169)}$ = 3.79, p < .05, η^2 = .024). The age differences found in the exploratory analysis are illustrated in Figure 4.

Discussion

To the best of our knowledge, the present study is among the first in Information Systems (IS) research that examines different types of service

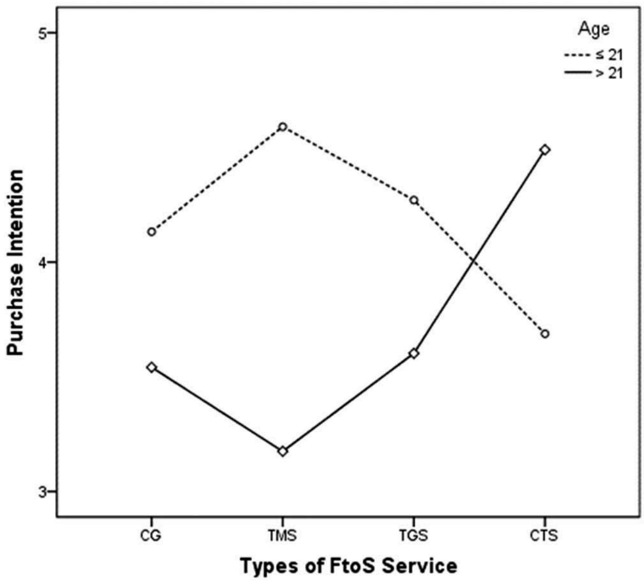


Figure 4. Interaction Effect of Age Groups with Type of FtoS Service.
Notes: FtoS = face-to-screen; CG = control group; TMS = technology-mediated service; TGS = technology-generated service; CTS = comprehensive technological service.

in m-commerce to leverage the purchase intention of complex products. As a key outcome, we provide new insights on the mechanisms determining consumers' needs for specific configurations of service in m-commerce. The results extend the knowledge on FtoS services as a means to increase the willingness to purchase complex products via mobile devices, by showing that the integration of TMS and TGS can reduce the disadvantages of both. Our investigation showed that a TGS and, in particular, a CTS foster a positive estimation of service quality. A CTS also exhibits a positive impact on information quality and significantly lowered the perceived performance risk in contrast to a TMS. This implies that a combination of the services is needed to reduce the estimation of severe hazards; for instance, those experienced through product malfunctioning. It was also shown that the highest perceived financial risk is caused by the human-based TMS while the technical service rendered the lowest perception of financial risk. As argued above, this gives rise to the assumption that human components in service provision can even engender higher cost estimations. On the other hand, a TGS has 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. Moreover, a TMS imposes the highest psychological risks while a CTS reveals the lowest. This result supports the hypothesized increase of discomfort and inconvenience by the integration of a TMS while a TGS does not substantially alter the perception of psychological risks. Although, PU, PEOU, and PI were not influenced by the type of service in our main investigation, subsequent exploratory analyses confirmed a general positive increase for PEOU and PI leveraged by a CTS under exclusion of the age group of 19 years old and younger. The results substantiate our assumption about consumers' preferences for mere technological service if they have the choice between a TMS and a TGS. Nonetheless, overall, consumers prefer the integration of human components as a safeguard to the pure technology-based service. To summarize, all hypothesized effects were in the predicted direction, and they corresponded to the theorizing here. Higher-order effects (i.e., interactions) helped to explain some of the effects in greater depth, as shown for the example of age.

Theoretical Implications

The present research obtained valuable contributions for the understanding of consumers' purchase intention for complex products using FtoS services in m-commerce. In particular, there are five major implications for theory: First, prior literature revealed discordance about the benefits of using technology-based services as an augmentation to personal service encounters [26, 42, 73, 74]. While some studies found mainly positive relations [8, 94], others indicated a more complex pattern, some of which also included negative effects [42, 59, 74]. Our results support a differentiated view of service migration in an FtoS service context and provide evidence that personal service can even inhibit m-commerce purchases under certain conditions. Our research attenuates the importance of personal service in m-commerce and accentuates the role of technological service. The findings further implicate that there are no standard formulas for the appropriate deployment of personal and technological service, but that there is a need for a thorough balancing of both. This corresponds with Dabholkar's [24] recommendations to generally provide consumers with full service options.

Second, this study adds depth to the understanding of the psychological mechanisms that are affected by FtoS services. The results leverage previous findings, supporting the importance of service and information quality as effective means to reduce uncertainties during the decision process [45, 75, 78, 100]. We suggest that service quality in the product encounter prior to the purchase can predominantly be enhanced by elaborating on a TGS. However, this carries the risk of higher time effort for consumers. In contrast, a TMS alone revealed detrimental effects on performance risk, financial risk, and psychological risk. Our findings offer new knowledge of how to counteract these mechanisms, as often requested in the literature [19, 40, 59, 86]. The insights support the need for a CTS as a requirement of high PEOU and purchase intention, although PU is not necessarily directly affected.

Third, the suggested concept of STF was supported 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 STF (CTS). This extends recent theorizing about the issue of coherence (in terms of fit) for the acceptance of IS [43, 67, 77]. Our results satisfy the demand for more research on information and service provision [21, 37].

Fourth, the vast majority of studies in this area have placed a strong focus on the moment of personal service interaction, but disregarded the initial contact with the sales technology [37, 42, 44]. We purposely joined this relevant moment in m-commerce when the purchase intention for complex products is still fairly low, by taking a first prototype-based approach toward a sales app, and excluding the actual encounter with service staff when using a TMS. This allows us to draw 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 consumer decision chain (e.g., ROPO). This is in line with current decision-making models [58], and contributes by giving more tangible insights into how to match consumers' decision steps with adequate service design. More specifically, initial decision steps such as the need for recognition, information search, and evaluation of alternatives should be well covered with a 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 a TMS. These insights might also help to reduce overblown technologies leading to frustration and irritation [50].

Finally, our results obtained exploratory insights into demographical differences with regard to consumer preferences for types of service in m-commerce. By taking into account the complexity of insurance policies, experience-related factors (i.e., age, self-efficacy, product knowledge) seem to alter the preference for a given service type. This is in line with several previous findings. According to Maity and Dass [67], little or no product knowledge increases the need for a TMS as complexity is rising. In turn, TGS may profit from the decrease of complexity with increasing product knowledge. Likewise, Gefen and Pavlou [40] argued that perceived trust and risk have little influence on users' decision making when the institutional structures are perceived to be poor. Perhaps young and unexperienced consumers do not even fully contemplate the transaction, resulting in indifference regarding the risk estimation regardless of the condition. This is supported by the significant difference in our exploratory result for the older age group concerning performance risk and purchase intention. To make more reliable predictions, future research should account for person-specific life cycle changes (e.g., in a long-term study) and different age groups within a sample.

Practical Implications

Our results have important implications for companies that deal with sales of complex products to end users. First, we propose a comprehensive (hybrid) approach incorporating a TMS and a TGS, with placing particular priority on the TGS, as it shows a higher fit with m-commerce supported by a higher efficiency in reducing risks. It therefore encourages consumers to make a self-determined purchase and helps avoid inconvenient personal contact. Many

TGS functions (e.g., trust and test seals, video and audio product tutorials, info buttons) are already well established in other areas (e.g., in e-retail) and can easily be adapted to m-commerce. For a TMS, well-known service components include call, chat, e-mail support, and a location-based agency finder. However, there are many underutilized possibilities that need to be evaluated [50] such as audio and video chat, interconsumer service, and frequent broadcasts on online product presentations by experts.

Second, 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 [69]. Sales commissions should more often be turned into service commissions, which means basing the 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 sales staff in the insurance industry.

Third, m-commerce should be designed consistent to common decision processes of consumers [90]. Each page needs to be scanned for emerging risks and adapted accordingly by adding technological or personal service elements that altogether can help to form a particular website identity and thus increase repeat purchases [61]. However, the amount of available features to establish a sophisticated technological service is manifold [50], but still entails great potential for the future. The implementation of artificial intelligence—for example, chatbots and avatars as advisers (cf. virtual agents)—could improve the service experience of consumers and relieve service personal.

Finally, our results confirm considerable differences between different age groups, suggesting that service preferences vary along with the amount of product experience and other individual characteristics [30, 37, 46]. The accentuation of human interaction should thus differ according to the experience level that a consumer states. These insights are particularly important since they can help to overcome existing deficits in the perceived provider benevolence in m-commerce [4].

Limitations and Future Research

Our research has limitations, which provide opportunities for future research. Clearly, our labor-intensive experimental procedure has led to restrictions in sample size, participant diversity, and the number of implemented treatments. We thus were not able to analyze differences across factors such as gender or experience in greater detail. This gives rise to a more detailed investigation of demographical, sociographical, and cultural attributes. For example, Ward and Lee [101] 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. Although insurance is a prime example of a complex product with currently high purchase resistance in m-commerce, the generalizability of our findings to other product categories or technologies should also be tested in future studies.

To our best knowledge, there is no classification of the value of different service features regarding their impact on users' purchase intention. The influence of FAQs, search function, assurance seals, and so forth, may vary in this respect. This can be augmented by also taking brand labels into consideration, as one of the main determinants in increasing trust and purchase intention [33, 46, 93], which might moderate the need for a TGS and TMS in particular. We therefore suggest a detailed investigation of the effects of different service features in future research.

By implementing different forms of service, which vary in the form of how technology is used to support sales of complex products, all of these arguably rely on their flawless technological execution. However, since we were interested in users' responses related to the less engineering-oriented variables of Web quality —service quality and information quality—we did not alter the underlying system and kept mobile as the static technology. However, we propose to extend our approach by combining the different types of service with alternating system components; for instance, by introducing different mobile devices or operating systems.

Our results provided 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 an FtoS service and should thus be subject to future investigations. We considered short-term insurance, which is less complex than life insurance, for instance. It can thus be presumed that different levels of product complexity might alter the need for interaction and thus the need for different types of service.

As noted, we focused on the prepurchase contact with sales technologies, but disregarded later steps in the purchase process. Prior studies have demonstrated that an oversupply of technological service elements on websites, such as trust seals, can even inhibit the purchase intention [40, 82]. This is especially relevant when consumers are already familiar with the sales environment and have established certain routines. Therefore, we presume that the provision of a TGS may be of particular relevance in early adoption stages, but can distract the user flow in later stages. In contrast, the importance of a TMS persists in the post-purchase or repeated purchase process since a TMS is rather used to support circumstances that are more complex. How to best balance the application of both types of service subject to the length of the usage periods should be determined in future investigations.

Conclusion

The present research revealed potential solutions to improve the current 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 technology. It was shown that m-commerce requires a high amount of technological service to improve the perceived service quality and mitigate risks. In combination with the provision of human-based service components, the 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 indicated further potential influence factors such as age. To summarize, these results suggest a more personalized configuration of mobile service to satisfy the individual consumer's need for service-technology fit.

NOTES

1 A summary of all acronyms can be found in online Appendix 1.
2 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.
3 Because 4 is the scale mean, this can be seen as critical threshold for purchases to take action. This is in line with findings from Gefen and Pavlou [40].

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Supplemental File

Supplemental data for this article can be accessed on the publisher's website.

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