Journal of Retailing and Consumer Services 53 (2020) 101983

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: http://www.elsevier.com/locate/jretconser

Retail in my pocket– replicating and extending the construct of service quality into the mobile commerce context☆

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ARTICLE INFO

Keywords:
Mobile service quality
Mobile commerce
Replication
Propensity score matching
Electronic service quality
Contextual factors

ABSTRACT

Nowadays, retailers are interested in how customer preferences regarding service quality are changing due to the adoption of different devices for shopping purposes in both the desktop and mobile contexts. To answer this question, this paper first replicates, in the mobile commerce (m-commerce) context, the results from Blut et al. (2015), who conducted a meta-analytic review of electronic service quality. Replication results question the robustness and generalizability of the conceptualization in the mobile service quality context. Thereby, practitioners and academics are encouraged to adapt a customer-centric approach in organizing marketing practices. The replication extends the conceptualization of electronic service quality by considering a unique dimension named ubiquity of services, defined as the retailer's ability to provide offers based on location and time. To reveal psychological mechanisms explaining the results of the replication study, a follow-up study draws on these contextual factors. In this context, this study uses a quasi-experimental approach by utilizing propensity score matching to account for self-selection effects to examine differences between desktop and mobile device users. As a result, this research contributes to the literature by identifying contextual boundary conditions regarding the shopping trip intentions and risk perceptions of mobile device users and desktop device users. Based on the results, major implications for retailers and further research are given.

1. Introduction

Nowadays, retailers are interested in how customer preferences regarding service quality are changing due to the adoption of different devices for shopping purposes in both the desktop and mobile contexts (e.g., Kannan and Li, 2017; Kumar, 2018; Marketing Science Institute, 2018; Souiden et al., 2018). Whereas the desktop context is mainly represented by laptops and desktop computers, customers are increasingly using smartphones and tablets as primary devices for shopping in the mobile context (Criteo, 2018). This classification is reasonable, since recent research indicates that tablets act as complementary devices for smartphones and as substitutes for laptop or desktop computers, respectively (Xu et al., 2017). In order to better understand and satisfy customer needs, and therefore to generate greater revenue, retailers are advised to adopt a customer-centric approach in organizing their marketing practices around distinct customer groups (e.g., mobile device users and desktop device users) rather than product categories (Althuizen, 2018; Crecelius et al., 2019). Consequently, the main goal of this research is to compare shopping trip perceptions and intentions of e– and m-commerce users in order to enable customer-centric marketing practices. To achieve this goal, a replication study and a follow-up study will be conducted.

First, the replication study is justified by the rise of mobile devices as primary shopping device (Criteo, 2018). In this context, retailers are still struggling to deliver satisfactory levels of mobile service quality (MSQ), resulting in lower conversion rates and higher shopping cart abandonment rates compared to the electronic counterpart (de Haan et al., 2018; Huang et al., 2018; Kaatz et al., 2019). While substantial attention has been paid to electronic service quality (ESQ) perceptions for traditional e-commerce settings, existing research on MSQ is still characterized by a high level of fragmentation and single-study observational models (Blut et al., 2015; Ladhari, 2010; Lamberton and Stephen, 2016; Lemon and Verhoef, 2016; Yadav and Pavlou, 2014). On the one hand, it heavily concentrated on different contexts, such as mobile health services (e.g., Meigounpoory et al., 2014; Akter et al., 2010) or mobile brokerage services (e.g., Lu et al., 2009). On the other hand, replication approaches with a retailing focus did not consider factors that are specific to shopping with a mobile device (e.g., Huang et al., 2015; Vlachos et al., 2011),

☆ Paper to be submitted to the Journal of Retailing and Consumer Services.

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https://doi.org/10.1016/j.jretconser.2019.101983
Received 13 March 2019; Received in revised form 2 September 2019; Accepted 22 October 2019
Available online 4 November 2019

failing to incorporating advances in literature (Bettis et al., 2016). Additionally, as demonstrated by Blut et al. (2015), who conducted a meta-analytic review of ESQ, these works focused on measurements of ESQ that were outperformed by a four dimensional conceptualization, including the dimensions of website design, fulfillment, customer service, and security/privacy. Hence, this research intends to contribute to the literature by replicating the results of Blut et al. (2015) into the m-commerce context, extending the conceptualization by one factor. Thereby, this research is conducted as a duplication that serves to examine the robustness and generalizability of the four-dimensional conceptualization of ESQ (Bettis et al., 2016; Brock et al., 2013) and by implementing a unique dimension for MSQ, the scope and limits of the original study can be determined (Bettis et al., 2016; Eisend et al., 2016).

In this context, the contextual marketing theory postulates a shift from content marketing (e-commerce) to contextual marketing (m-commerce), which refers to the ability to design offers based on what the customer is doing as well as when and where the customer is doing it (Kenny and Marshall, 2000). Thus, mobile device users benefit from the *ubiquity of services*, which describes the possibility of shopping without spatial and temporal constraints (de Haan et al., 2018; Kenny and Marshall, 2000; Kleijnen et al., 2007). This dimension represents the key to success in m-commerce, because being capable of delivering pertinent information that is specific to a particular location or time is associated with higher value perceptions of m-commerce users (Ko et al., 2009). Because Kannan and Li (2017) determine interactions between devices and contextual factors as an important area of research, the four-dimensional conceptualization of ESQ will be extended by the dimension *ubiquity of services*. Hence, by applying structural equation modeling, the replication study intends to answer the following research question:

> ***Research question 1.*** *How are electronic service quality dimensions and the ubiquity of services dimension related to service quality in the m-commerce context?*

Since replication studies are most effective in linkage with a follow-up study (Bettis et al., 2016) and to reveal psychological mechanisms explaining the results of the replication study, a second study is conducted applying contextual marketing theory (Kenny and Marshall, 2000) in combination with construal level theory (see Fig. 1). The latter proposes that shopping trip intentions as well as perceptions of customers differ under varying contextual factors, namely spatial and temporal conditions (Trope and Liberman, 2010). Hence, the contextual factors study intends to contribute to the literature by revealing differences between mobile device users and desktop device users regarding their shopping behavior. This knowledge is essential for retailers, because given customers' consumption of information across different devices and increased targeting capabilities for retailers, it is still questionable when, where, and how best to reach customers (Marketing Science Institute, 2018). In this context, a quasi-experimental approach is utilized, using propensity score matching to account for self-selection effects. Hence, the contextual factor study is motivated by the following research question, which will be tested by a series of t-tests and covariance analyses:

> ***Research question 2.*** *With regard to the ubiquity of services, which is the right device based on location and time to reach a customer?*

2. Theoretical framework

2.1. Theoretical discussion on the construct of service quality

The first two decades of research on service quality in a brick-and-mortar setting have to be described as divergent. The biggest discussion aroused about the measurement of the service quality construct. The first research stream was of the opinion that perceptions of service quality result from the disconfirmation paradigm (e.g.,Churchill and Suprenant, 1982), according to which customers compare their expectations of the service with the perceived performance (e.g., SERVQUAL: Parasuraman et al., 1988). Especially SERVQUAL was not only criticized because of its perception-minus-expectation measurement of service quality, but also because replications revealed its inconsistent factor structure (e.g., Carman, 1990; Cronin Jr. and Taylor, 1992). The second research stream followed the approach of evaluating service quality on a performance-based measurement (e.g., SERVPERF:Cronin Jr. and Taylor, 1992), whose advantageousness has been demonstrated empirically

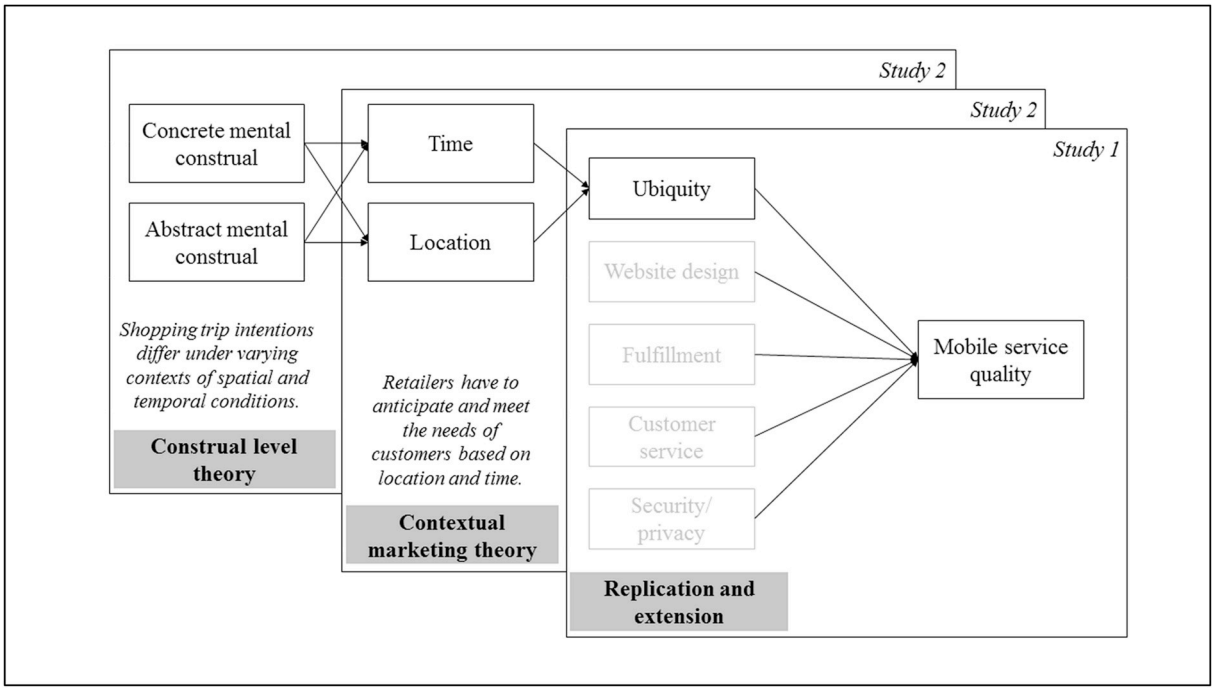

Fig. 1. Theoretical framework.

and conceptually over time (e.g., Babakus and Boller, 1992; Boulding et al., 1993; Cronin Jr. and Taylor, 1994). As a synthesis and extension of different perspectives, a measurement finally emerged, which found evidence that customers form their service quality perceptions based on the evaluation of three primary dimensions: (1) interaction service quality, (2) physical environment quality, and (3) outcome quality (Brady and Cronin Jr., 2001). Therefore, in a brick-and-mortar setting, individually service encounters represent the foundation for business success, since most customers interact with a firm through their frontline employees. Hence, individual service encounters are supposed to be the key element in brick-and-mortar settings, since positive service encounters influence customer's satisfaction, repurchase intention, and positive WOM, whereas negative service encounters will lead to increased costs for compensation, repeated services, or negative WOM (Bitner, 1990; Bitner et al., 2000).

The rise of the Internet as sales and distribution channel initiated the second phase of service quality research, which was supposed to revolutionize the temporal dimension of shopping, enabling retailers to deliver content marketing. At the same time, it also poses greater risk perceptions and privacy issues because of the less interpersonal contact (Blut et al., 2015). Early adopters of ESQ research tried to replicate results from non-internet service quality research. The results demonstrated that dimensions either cannot be not transposed to the context of e-commerce or that their relative importance changes when service is delivered through technology (Parasuraman and Grewal, 2000). For instance, quality dimensions referring to the physical environment of service quality (e.g., Brady and Cronin Jr., 2001; Parasuraman et al., 1988) needed to be replaced by dimensions concerning the website design (van Riel et al., 2001). Furthermore, because of the less personal contact with service employees, dimensions concerning the interaction quality of a service encounter (e.g., Brady and Cronin Jr., 2001; Parasuraman et al., 1988) were less important in the context of e-commerce (Gefen, 2002).

As a result, several studies tried to develop new measurement scales for ESQ encompassing factors that are unique for e-commerce (e.g., SITEQUAL: Yoo and Donthu, 2001; ISRQ: Janda et al., 2002; WebQual: Loiacono et al., 2002; eTailQ: Wolfinbarger and Gilly, 2003; E-S-QUAL: Parasuraman et al., 2005). Ultimately, this research phase was merged by Blut et al. (2015), who conducted a meta-analytic review on ESQ using 89 independent samples representing 31,264 individual observations. Their results demonstrated that ESQ has basically four underlying dimensions, namely (1) website design, (2) fulfillment, (3) customer service, and (4) security/privacy (Blut et al., 2015). This four-dimensional conceptualization was later confirmed by Blut (2016).

The third phase of research on service quality was ushered in by the introduction of mobile devices as a shopping device. In addition to the temporal dimension of shopping, it is particularly the spatial dimension of shopping that is to be revolutionized. Since the importance of replications for research on the construct of service quality has been demonstrated, research on MSQ has to test the applicability of the ESQ conceptualization in the context of m-commerce, as it has hardly been done in literature so far (Huang et al., 2015; Vlachos et al., 2011). In a MSQ context, it is assumed that ESQ dimensions also matter for mobile customer perceptions, but to a different extent. Additionally, a replication needs to incorporate factors that are unique to the m-commerce context (Bettis et al., 2016).

2.2. Contextual marketing theory

With the introduction of mobile devices as a retailing channel, geographical boundaries in particular were blurred (Kumar, 2018). As a result, shopping with mobile devices is characterized by greater flexibility, personalization, interactivity, and localization of services (e.g., Hubert et al., 2017; Kleijnen et al., 2007; Ko et al., 2009). These characteristics enable the possibility of real-time marketing without temporal and spatial constraints. These time- and location-sensitive advantages of m-commerce are summarized as *ubiquity of services* (Kleijnen et al., 2007).

Drawing on contextual marketing theory (Kenny and Marshall, 2000), which essentially predicted a much-needed shift of retailers' marketing efforts from content dependent to context dependent, it is suggested that the location of the customer and the time of day could be important predictors of customers' shopping behavior (Canova and Nicolini, 2019; Goodman and Malkoc, 2012; Kannan and Li, 2017; Luo et al., 2013). As a result, mobile devices enable retailers to reach their customers whenever and wherever they are ready to purchase, creating a ubiquitous agent that accompanied the customer (Kenny and Marshall, 2000).

Consequently, as seen in Fig. 2, the four-dimensional conceptualization of ESQ is extended by including a unique dimension named ubiquity of services and a positive impact on overall MSQ is assumed. Hence:

Hypothesis 1. Perceptions of (a) ubiquity, (b) website design, (c) fulfillment, (d) customer service, and (e) security/privacy contribute directly to overall perceptions of MSQ.

According to the technology acceptance model (TAM; Davis, 1989), shopping trip intentions are dependent on the perceptions of ease of use and usefulness of the device for shopping purposes. As discussed earlier, mobile device users especially appreciate the ubiquitous nature of m-commerce, increasing their ease of use perceptions compared to desktop device users, which in turn will affect behavioral intentions more positively (Hubert et al., 2017; Kleijnen et al., 2007). As a result, m-commerce is considered to have the potential of improving the efficiency and service quality of retailers, and to provide unique value propositions to customers (Kumar, 2018).

In contrast, perceptions of usefulness are supposed to be impacted negatively by different facets of risk (Kleijnen et al., 2007; Xu et al., 2017), by which desktop device users are not affected. Compared to desktop devices, mobile devices are equipped with smaller screen sizes and input buttons, increasing perceptions of performance risk (Ghose et al., 2013; Xu et al., 2017). Furthermore, mobile devices are trackable via the Global Positioning System (GPS), increasing customers' security and financial risk perceptions, because opportunities for misusing personal data are more present (Kumar, 2018).

Surprisingly, those facets of risk are not considered as a barrier to mobile commerce adoption; moreover, mobile customers are concerned about the greater cognitive effort m-commerce requires (Ghose et al., 2013; Kleijnen et al., 2007). Additionally, since ease of use has a direct positive influence on shopping trip intentions (Davis, 1989), the literature suggests that contextual factors offer such an advantage for mobile device users that even significantly higher risks are accepted (de Haan et al., 2018; Xu et al., 2017). Hence:

Hypothesis 2. In a shopping context, mobile device users have greater (a) performance risk perceptions, (b) security risk perceptions, and (c) financial risk perceptions than desktop device users.

Hypothesis 3. In a shopping context, mobile device users have higher (a) purchase intention and (b) willingness to pay than desktop device users.

2.3. Construal level theory

Additionally, contextual marketing theory suggests an interaction effect between temporal or spatial boundary conditions and different devices on customer behavior. Retailers that are able to anticipate the needs of their customers based on location and time will be able to influence their decision making positively, and ultimately to become valued partners (Kenny and Marshall, 2000). The underlying psychological mechanism is grounded in construal level theory (Trope and Liberman, 2010). According to the theory, customers can form different mental construal, which impact their purchase decisions differently. In

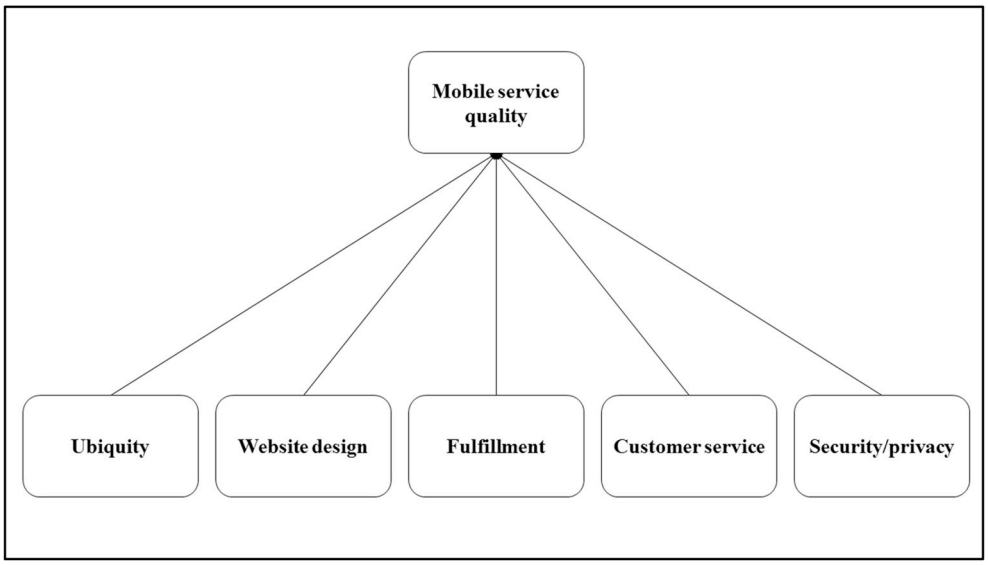

Fig. 2. Conceptual model of MSQ (Study 1).

this context, a more concrete mental construal induces higher involvement and purchase intentions, whereas a more abstract mental construal induces decreased purchase intentions. Luo et al. (2013) applied construal level theory in the mobile retailing context and revealed that lower locational and temporal distances induce mobile users to construe shopping tasks more concretely, thus increasing their purchase intentions.

2.3.1. Location of the user

In order to apply construal level theory, it is necessary to conceptualize the spatial distance to the shopping task. As demonstrated by recent research, shopping in public locations is perceived as more useful than shopping at more private locations, such as at home (e.g., Banerjee and Dholakia, 2008; Danaher et al., 2015; Fong et al., 2015). This is reasonable, since customers on the way benefit from synergies offered by mobile devices and traditional retail stores (Fong et al., 2015; Souiden et al., 2019). Thus, according to construal level theory, if customers are at home, they perceive a greater distance to their shopping task than customers on the way. In combination with contextual marketing theory, construal level theory assumes that customers on the way focus more on contextualized benefits and form a more concrete mental construal, whereas customers at home form a more abstract mental construal, leading to increased and decreased purchase intentions, respectively (Kenny and Marshall, 2000; Trope and Liberman, 2010).

With regard to differences between mobile device users and desktop device users, geo-conquesting is considered to be becoming a popular marketing tool as it ensures marketing's effectiveness. It enables retailers to provide relevant content and personalized messages in real time, improving the shopping experience at each touchpoint on the path to purchase (Kumar, 2018; Souiden et al., 2019). In this context, recent research shows that mobile device users on the way have higher purchase intentions and are willing to spend more due to the increased amount of time they spend on the shopping task. In this time, mobile customers are more likely to divert from their conventional shopping loop and to spend more for unplanned purchases (e.g., Calvo-Porral and Lévy-Mangin, 2019; Grewal et al., 2018; Hui et al., 2013).

Simultaneously, mobile device users' risk perceptions are increasing on the way. Research on contextual targeting demonstrates that ineffectiveness of advertising is a result of feelings of obtrusiveness, which are driven by privacy concerns (Goldfarb and Tucker, 2011). Particularly, mobile device users are afraid of retailers misusing data received from GPS, increasing their security and financial risk perceptions on the way (Kumar, 2018). Hence:

Hypothesis 4. The difference in mean between mobile device users and desktop device users regarding (a) performance risk perceptions, (b) security risk perceptions, and (c) financial risk perceptions increases when participants are on the way, whereas it decreases at home.

Hypothesis 5. The difference in mean between mobile device users and desktop device users regarding their (a) purchase intention and (b) willingness to pay increases when participants are on the way, whereas it decreases at home.

2.3.2. Time of day

In order to apply construal level theory, it is necessary to conceptualize the temporal distance to the shopping task. Literature indicates that foot traffic in shopping malls is highest in the afternoons (e.g., Calvo-Porral and Lévy-Mangin, 2019; Danaher et al., 2015) and casual browsing sessions are highest in the evening (Xu et al., 2017), representing customers' favorite times for shopping. Furthermore, customers are facing bounded intervals of time during working hours, in which they perform fewer tasks and are less likely to engage in cognitive effort (Tonietto et al., 2019). Thus, according to construal level theory, if customers are confronted with a shopping task during working hours (6 am–3 pm), they perceive a greater distance to the shopping task than customers during leisure hours (3 pm to midnight). In combination with contextual marketing theory, construal level theory assumes that customers during leisure hours focus more on contextualized benefits and form a more concrete mental construal, whereas customers during working hours form a more abstract mental construal, leading to increased and decreased purchase intentions, respectively (Kenny and Marshall, 2000; Trope and Liberman, 2010). Additionally, for customers confronted with a shopping task during working hours, the options to be observed will seem similar and interchangeable, decreasing their willingness to pay (Goodman and Malkoc, 2012).

With regard to differences between mobile device users and desktop device users, recent research demonstrates that tablets and smartphones act as complements during leisure hours, whereas tablets substitute for desktop devices. The latter substitutional effect is not apparent during working hours (Xu et al., 2017). Hence, mobile device activity is likely to increase during leisure time, whereas desktop device activity is higher during working hours (Canova and Nicolini, 2019). In addition, mobile devices act as substitutes for desktop devices for products which are high in time criticality and low in information intensity (Bang et al., 2013). Finally, customers are more susceptible to mobile advertising in crowded places because of mobile immersion (Andrews et al., 2016), which is

most likely to happen in leisure hours. Thus, shopping trip intentions are likely to increase for mobile device users during leisure hours, whereas they decrease for desktop device users.

Simultaneously, as mentioned earlier, the usage of mobile devices for shopping purposes is inextricably linked with higher risk perceptions, which additionally are not linked with desktop devices. Therefore, during leisure hours, mobile users are more likely to perceive increased risks. Hence:

Hypothesis 6. The difference in mean between mobile device users and desktop device users regarding (a) performance risk perceptions, (b) security risk perceptions, and (c) financial risk perceptions increases when participants shop during leisure hours, whereas it decreases during working hours.

Hypothesis 7. The difference in mean between mobile device users and desktop device users regarding their (a) purchase intention and (b) willingness to pay increases when participants shop during leisure hours, whereas it decreases during working hours.

The context of Study 1 enables the testing of H1, whereby research question 1 will be answered. The context of Study 2 enables the testing of H2–H7, answering research question 2. Next, both studies are described and their results are discussed.

3. Study 1: replication study

3.1. Survey data collection and measurement reliability

The purpose of the first study was to replicate findings regarding ESQ in the m-commerce context. This kind of replication studies generally tries to examine whether the definitions or relative importance of dimensions will change in the new context (Parasuraman and Grewal, 2000). In this context, this study is conducted as a duplication that serves to examine the robustness and generalizability of the four-dimensional conceptualization of ESQ (Bettis et al., 2016; Brock et al., 2013). Additionally, by implementing a unique dimension for MSQ, the scope and limits of the original study can be determined (Bettis et al., 2016; Eisend et al., 2016). In total, 188 undergraduate students experienced in m-commerce were recruited from a university in Germany to participate in the study. Student participants are appropriate for the purpose of this study since basic research and theory application require homogenous samples (Calder et al., 1981; Kardes, 1996). They were instructed to complete the survey with respect to their most recent shopping experience with a mobile device. The final sample consisted of 42.6% females with a mean age of 22.01 years (standard deviation [SD] = 3.197). The youngest participant was 18 years old, while the oldest participant indicated an age of 34 years. Most of the participants used a smartphone (66.3%) for their last shopping encounter, while the remaining participants (33.7%) used tablet computers.

In order to replicate the results of Blut et al. (2015), established scales from the e-commerce context were adapted. The website design and customer service dimensions were derived from Wolfinbarger and Gilly (2003), whereas the fulfillment and security dimensions were derived from Parasuraman et al. (2005). The ubiquity dimension was adapted from Ko et al. (2009). To measure the dimensions of MSQ, five-point Likert scales with the anchors 1 (strongly disagree) to 5 (strongly agree) were used. To reduce the risk of potential common method bias in advance, the design of the questionnaire was adjusted accordingly. For this reason, the dependent variable overall MSQ was measured by a semantic differential. The scale was adapted from Wolfinbarger and Gilly (2003). Additionally, respondent anonymity was ensured, independent and dependent variables were separated into different sections, and the survey contained reverse-coded items (Kortmann, 2014).

To assess the measurement reliability of the constructs, Cronbach's alpha (CA), composite reliabilities (CR), and average variances extracted (AVE) were calculated. All the constructs, except for the website design dimension, showed CA scores exceeding the threshold value of 0.70 (Nunnally, 1978), CR scores exceeding the threshold value of 0.60 (Bagozzi and Yi, 1988), and AVE scores exceeding the threshold value of 0.50 (Fornell and Larcker, 1981). Furthermore, according to the Fornell and Larcker (1981) criterion, the result of the test for discriminant validity was satisfactory (see Table 1 and Table 2).

With regard to website design, the construct's measurement properties proved to be inadequate. Especially the insufficient AVE score means that the greater amount of the variance of website design is captured by the measurement error (Fornell and Larcker, 1981). Nevertheless, since the website design dimension is an important construct for replication purposes, the construct was not excluded from testing.

3.2. Results and discussion

To examine the impact of MSQ dimensions on overall perceptions of MSQ, structural equation modeling was employed using the MPLUS software package. As the estimator, maximum-likelihood estimation with robust standard errors was used, because this estimation is considered to be robust to non-normality (Muthén and Muthén, 2017). The fit criteria indicate that the proposed model fits the data well (χ^2 df:115 = 171.573; comparative fit index [CFI] = 0.950; Tucker Lewis index [TLI] = 0.934; root mean square error of approximation [RMSEA] = 0.051; standardized root mean square residual [SRMS] = 0.051), but comparing the model fit with criteria reported by Blut et al. (2015), the ESQ model (e.g., CFI = 1.000; RMSEA = 0.017) shows better fit than the MSQ model.

The results confirm four of the five dimensions of MSQ. As seen in Table 3, ubiquity ($\beta = 0.213$, $p < .05$), website design ($\beta = 0.290$, $p < .01$), fulfillment ($\beta = 0.227$, $p < .05$), and security ($\beta = 0.204$, $p < .05$) are associated with overall perceptions of MSQ, whereas customer service ($\beta = 0.096$, $p > .05$) does not impact perceptions of overall MSQ. Hence, hypotheses H1(a), (b), (c), and (e) are supported, while H1(d) is not. Overall, the model explains 48.5% of the variance in overall MSQ.

In comparison to ESQ, the results indicate that perceptions regarding customer service only contribute to ESQ perceptions and that perceptions regarding security only matter for MSQ perceptions, whereas website design and fulfillment are associated with both ESQ as well as MSQ perceptions. In addition, the study found a unique dimension, ubiquity of services, impacting MSQ perceptions positively. To estimate differences regarding the importance of dimensions between ESQ and MSQ, it tested whether the path coefficients in the MSQ model significantly differ from the path coefficients reported in Blut et al.'s (2015) meta-analysis on ESQ. After receiving the standard errors of interest and the harmonic sample size for the meta-analysis (3,244), a *t*-test using the formula discussed by Brock et al. (2013) was employed:

Table 1
Discriminant validity of latent constructs (Study 1).

	1	2	3	4	5	6
1 Ubiquity	**.751**					
2 Website design	.428	**.633**				
3 Fulfillment	.456	.385	**.775**			
4 Security	.069.	.247	.192	**.807**		
5 Customer service	.104	.322	.308	.425	**.734**	
6 MSQ	.465	.550	.505	.375	.368	**.764**

Note: Bold numbers on the diagonal show the square root of the average variance extracted (AVE); numbers below the diagonal represent construct correlations.

Table 2
Measurements reliabilities (Study 1).

Construct	Items		Factor loadings	Reference	CA	CR	AVE
Ubiquity	UBI1	The mobile store was accessible at any time.	.73	Ko et al. (2009)	.789	.795	.564
	UBI2	The mobile store was accessible at any place.	.70				
	UBI3	It provided real-time information about content I was interested in.	.82				
Website design	WD1	The mobile store provided in-depth information.	.56	Wolfinbarger and Gilly (2003)	.654	.666	.401
	WD2	It was easy to complete the transaction at the mobile store.	.62				
	WD3	The level of personalization at the mobile store was about right.	.71				
Fulfill-ment	FF1	My order was delivered when promised.	.70	Parasuraman et al. (2005)	.811	.816	.600
	FF2	My order was available for delivery within a suitable time frame.	.89				
	FF3	My order was delivered quickly.	.73				
Customer service	CS1	The mobile store was ready to respond to my needs.	.70	Wolfinbarger and Gilly (2003)	.774	.778	.539
	CS2	When I had a problem, it showed a sincere interest in solving it.	.79				
	CS3	The mobile store answered inquiries promptly.	.72				
Security/privacy	SEC1	The mobile store protected information about my transaction.	.84	Parasuraman et al. (2005)	.847	.848	.651
	SEC2	It did not share personal information with other stores.	.76				
	SEC3	The mobile store protected information about my credit card.	.82				
Mobile service quality	MSQ1	Poor to excellent.	.85	adapted from Wolfinbarger and Gilly (2003)	.797	.806	.584
	MSQ2	Inferior to superior.	.76				
	MSQ3	Low quality to high quality.	.67				

Note: AVE, average variance extracted; CA, Cronbach's alpha; CR, composite reliability.

Table 3
Structural equation results of Study 1 in comparison to Blut et al. (2015).

	Study 1		Blut et al. (2015)		Differences	
	β_{MSQ}	S. $E._{MSQ}$	β_{ESQ}	S. $E._{ESQ}$	$\Delta_{MSQ-ESQ}$	t
Ubiquity → MSQ	213*	.101	–	–	–	–
Website design → MSQ	.290**	.110	.196**	.017	.094$^{n.s.}$	1.247
Fulfillment → MSQ	.227*	.112	.248**	.017	-.021$^{n.s.}$	−0.278
Customer service → MSQ	.096$^{n.s.}$	.102	.211**	.016	–	–
Security → MSQ	.204*	.087	.014$^{n.s.}$	.015	–	–
R^2 (Overall service quality)	.485		.348		.137	

Note: *p < .05; **p < .01; MSQ = mobile service quality; ESQ = electronic service quality.

$$t = \frac{Path_{MSQ} - Path_{ESQ}}{\left[\sqrt{\frac{(n_{MSQ}-1)^2}{(n_{MSQ}+n_{ESQ}-2)} * S.E._{MSQ}^2 + \frac{(n_{ESQ}-1)^2}{(n_{MSQ}+n_{ESQ}-2)} * S.E._{ESQ}^2}\right] * \left[\sqrt{\frac{1}{n_{MSQ}} + \frac{1}{n_{ESQ}}}\right]} \quad (1)$$

For both path coefficient pairs 'website design on overall service quality' ($\beta_{MSQ} = 0.290$ vs. $\beta_{ESQ} = 0.196$; Δ path coefficients = .094; $p > .05$) and 'fulfillment on overall service quality' ($\beta_{MSQ} = 0.227$ vs. $\beta_{ESQ} = 0.248$; Δ path coefficients = −0.021; $p > .05$), no significant differences in mean were found. Hence, this result indicates that both dimensions in the mobile as well as desktop context matter equally to service quality perceptions.

Consequently, the results demonstrate that differences between the perceptions of ESQ and MSQ mainly refer to the ubiquity of services and the security dimension. To reveal psychological mechanisms explaining the results of the replication study, the follow-up study draws on contextual factors, namely location and time. In this context, the follow-up study attempts to identify contextual boundary conditions to show when and where the differences between mobile device users and desktop device users occur.

4. Study 2: contextual factors study

4.1. Survey data collection and measurement reliability

The purpose of this study was to derive differences between mobile device users and desktop device users regarding their risk perceptions and shopping trip intentions, respectively, particularly depending on the time of the day and the location of the customer. Participants were asked to answer an online survey with respect to the device they were using, the location they were at, and the time they started the survey. The first part of the questionnaire comprised contextual factors, asking participants to describe their current location and to indicate their habit with the device used. An exact timestamp was automatically generated by the survey provider. In the second part of the survey, participants were asked to imagine collecting information about new shoes, comparing alternatives, and finally buying them at that very moment. Shoes were chosen as a product because they are of a high-involvement and utilitarian nature (Danaher et al., 2015), a necessary requirement for mobile display advertising campaigns to be successful in increasing customers' purchase intentions (Bart et al., 2014). In spite of this, shoes are not considered to be a risky product category and both device groups are considered to be equally experienced with the product, so that it is unlikely that mobile devices or desktop devices are undervalued or overvalued, respectively (de Haan et al., 2018). Afterwards, participants answered questions about their anticipated risk perceptions and shopping trip intentions. At the end, personal information was requested. Fig. 3 summarizes the methodological approach of Study 2.

Participants were not randomly assigned to a device category, but self-selected into either the experimental group (mobile device users) or control group (desktop device users) due to the device they used to complete the survey. To account for self-selection bias, propensity score matching was employed to create an artificial control group of statistical twins for the experimental group (e.g., Bommaraju and Hohenberg, 2018; Janakiraman et al., 2018).

In the first step, a set of theoretical related matching variables were identified that explain participation in the experimental group. In this context, habit with the device used, ease of use of the device, usefulness of the device for shopping purposes, location of the participant, time of day, age of the participant, and gender of the participant served as

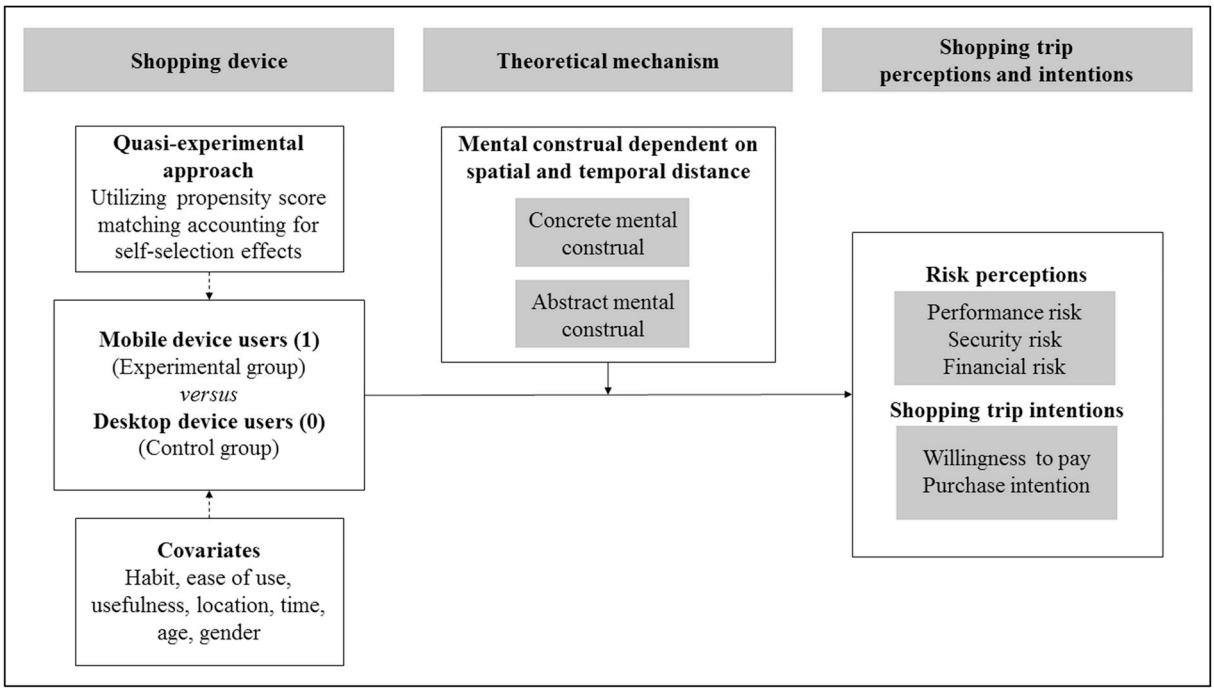

Fig. 3. Conceptual model and methodological approach (Study 2).

covariates. Using the identified matching variables, binary logistic regression was employed to calculate a propensity score for all participants, indicating the probability of self-selection into the experimental group. In the second step, using their propensity score, the participants from the experimental condition were matched with their nearest neighbor in the control condition. In this context, a distance measure (a caliper of $d = 0.2$ standard deviations) of the propensity score was used to reduce bias between the two conditions (Stuart, 2010). Thus, each mobile device user had a statistical twin in the desktop device user group, who did not use a mobile device for the survey but had statistically the same propensity to do so.

After matching was completed, a series of model adequacy checks were performed to check whether the balance on the covariates had been reached. First, the result of an overall balance test following Hansen and Bowers (2008) suggested covariate balance given the non-statistically significant test result ($\chi 2(8) = 6.837$ ($p = .554$)). Second, following Iacus et al. (2009), relative covariate balance had been improved, since the $\mathscr{L}$-value was reduced from $\mathscr{L} = 0.994$ before matching to $\mathscr{L} = 0.991$ after matching. Third, no covariate exhibited a large imbalance ($|d| > 0.25$). Hence, covariate balance was assumed within the paired dataset. Consequently, differences between experimental group and control group disappeared (see Table 4).

Finally, in the third step, to test the proposed hypotheses, multivariate data analysis on both groups was performed. Fig. 4 summarizes the matching procedure.

Again, to reduce the risk of a potential common method bias in advance, the design of the questionnaire was adjusted accordingly. First, as seen in Table 5, the constructs were measured with 5-point Likert scales and semantic differentials. Second, respondent anonymity was ensured. Finally, independent and dependent variables were separated into different sections (Kortmann, 2014). As also seen in Table 5, all constructs were adapted from established scales. Willingness to pay (€) was included as an open question (Homburg et al., 2015). To assess the measurement reliability of the constructs, CA scores were calculated. Except for habit, all constructs showed CA scores exceeding the threshold value of 0.70 (Nunnally, 1978).

Table 4
Comparison of experimental and control group (Study 2).

	Mobile device users	Desktop device users	Δ	t
Demographics				
N	317	317	–	–
Mean age	24.23 years	24.08 years	$.15^{n.s}$	.301
Minimum age	18 years	18 years	–	–
Maximum age	61 years	56 years	–	–
Gender	65.9% male	63.4% male	–	–
Contextual factors				
Location: Home	226	238	–	–
Location: On the way	91	79	–	–
Time: Leisure hours	157	163	–	–
Time: Working hours	160	154	–	–
Covariates				
Habit	2.72	2.66	$.06^{n.s}$	.861
Ease of use	4.52	4.48	$.04^{n.s}$	.821
Usefulness	3.52	3.46	$.06^{n.s}$	.796

4.2. Results and discussion

To test H2 and H3, several t-tests were conducted, the results of which can be seen in Table 6. With regard to risk perceptions, significant differences in mean were found for perceptions of performance risk ($M_{MOB} = 2.623$; $M_{DESK} = 1.857$; $\Delta_{MEANS} = 0.766^{**}$; $t = 8.681$) and perceptions of security risk ($M_{MOB} = 3.138$; $M_{DESK} = 2.885$; $\Delta_{MEANS} = 0.253^{**}$; $t = 3.138$), in support of H2(a) and (b). Since differences in mean for perceptions of financial risk ($M_{MOB} = 3.003$; $M_{DESK} = 2.931$; $\Delta_{MEANS} = 0.072^{n.s.}$; $t = 0.939$) were not significant, H2(c) is not supported. With respect to shopping trip intentions, mobile users are willing to pay significantly more than desktop users ($M_{MOB} = 82.39$; $M_{DESK} = 73.34$; $\Delta_{MEANS} = 9.05^{**}$; $t = 3.214$) and also have significantly higher purchase intentions ($M_{MOB} = 3.538$; $M_{DESK} = 3.344$; $\Delta_{MEANS} =$

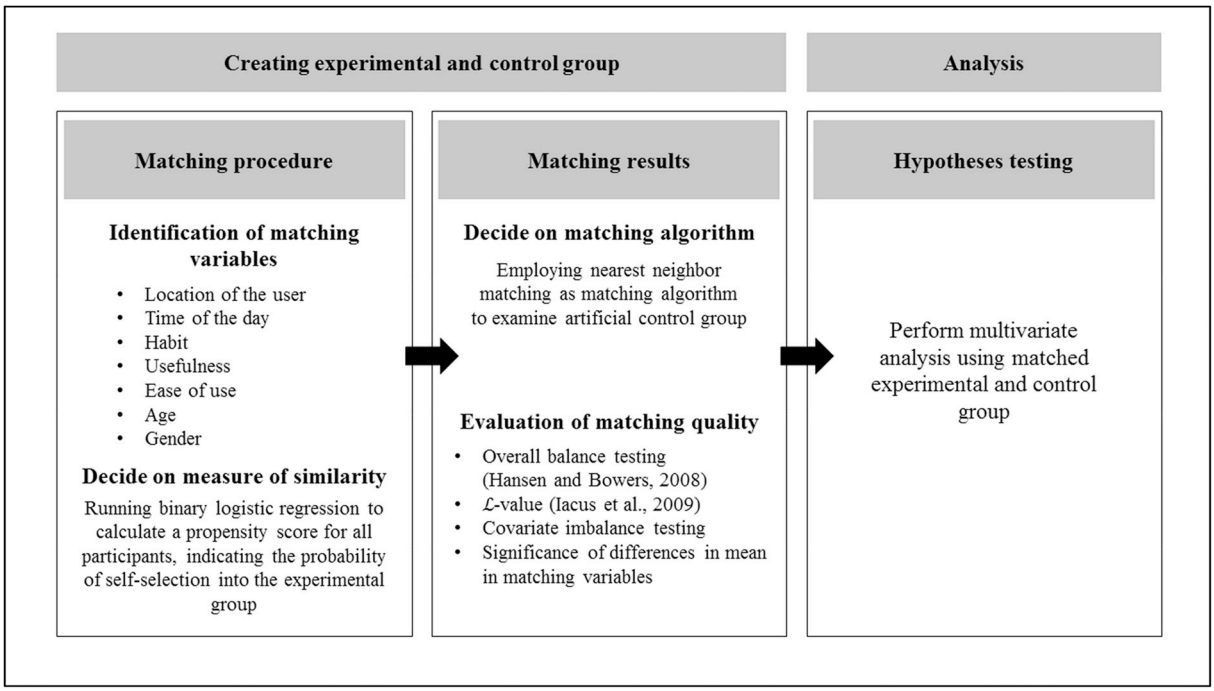

Fig. 4. Summary of the employed matching procedure (adapted from Wangenheim, and Bayón, 2007).

0.194**; t = 2.445), in support of H3(a) and (b).

Hence, although mobile users perceive significantly higher performance and security risks, they have a higher willingness to pay as well as purchase intention compared to desktop device users. It seems that the shopping outcome benefits (e.g., higher service quality) of contextual factors for mobile device users counter even significantly higher risks (de Haan et al., 2018; Venkatesh et al., 2017; Xu et al., 2017). An analysis of the location and the time of day as moderating variables follows to examine this assumption.

To test H4–H7, several covariance analyses were conducted. With regard to purchase intention, a significant interaction effect was found between location and mobile device (see Table 7; Fig. 5; device*location: $F = 4.228$; $p < .05$). The significant difference in purchase intentions between mobile and desktop device users examined in the previous *t*-test is confirmed only at home and disappears completely on the way. Accordingly, H5(a) is not supported, since the interaction has a negative effect on mobile device users' purchase intention on the way. This unexpected result might be described by mobile device users' risk perceptions. On the one hand, as shown in Table 7 and Fig. 6, a significant interaction between mobile devices and location impacts performance risk perceptions (device*location: $F = 4.815$; $p < .05$). Hence, if a mobile device user is on the way, generally higher perceived performance risks compared to desktop device users are further increased, in support of H4(a). On the other hand, with respect to perceptions of financial risk, a significant interaction was found between location and mobile device (see Table 7, Fig. 7; device*location: $F = 5.692$; $p < .05$). In general, the experimental and control groups do not perceive financial risks differently, but if mobile device users are on the way they have significantly higher financial risk perceptions, in support of H4(c). For willingness to pay and security perceptions, no significant interaction effects were found, not supporting either H4(b) or H5(b).

As shown in Table 8, no significant interaction between time of day and device regarding the dependent variables was found. Hence, time of day has no interactional impact on risk perceptions or shopping trip intentions between mobile and desktop device users, in support of neither H6 nor H7. This is reasonable, since both mobile and desktop devices enable the customer to shop on a 24/7 basis.

To conclude, the location of the user increased the risk perceptions of mobile device users compared to desktop device users, if the customers were on the way. At the same time, the purchase intentions of mobile device users decreased compared to desktop device users. Therefore, the additional mobility of mobile device users seems to impact customers negatively. According to Tarafdar et al. (2019), technologies such as mobile devices can be appraised as stressors based on, for instance, security issues, resulting in outcomes that are adverse consequences. Thus, it is possible that participants perceived the task as a location-incongruent shopping task. However, mobile device users were willing to pay more than desktop device users independent of location and time of day, indicating the potential of mobile customers for retailers' revenue.

5. General discussion

5.1. Theoretical contributions

This research replicated, refined, and extended the findings of Blut et al. (2015) in the m-commerce context. Based on the results of the replication study, a follow-up study was conducted to explore contextual boundary conditions for a needed customer-centric marketing approach. Hence, this research was motivated by two research questions, which will structure this section.

> ***Research question 1.*** *How are electronic service quality dimensions and the ubiquity of services dimension related to service quality in the m-commerce context?*

As indicated by structural equation modeling, the dimensions of (1) ubiquity, (2) website design, (3) fulfillment, and (4) security/privacy are positively related to perceptions of MSQ. In contrast, perceptions of customer service are not related to MSQ. Therefore, this research successfully extends the conceptualization of ESQ (Blut et al., 2015) and reveals a newly explored dimension named *ubiquity of services* (Bettis et al., 2016; Eisend et al., 2016).

With respect to the remaining dimensions, the replication finds conflicting results regarding the customer service and security/privacy dimensions compared to the original study. Hence, the conceptualization of ESQ struggles to discriminate between different devices (Bettis

Table 5
Measurements of study 2.

Construct	Items	Source	Cronbachs
Financial risk	When I used my [device] at the very moment I became concerned that … … the financial investment I would make would not be wise. … I really would get not my money's worth. … this could involve important financial losses.	adapted from Stone and Grønhaug (1993)	.757
Performance risk	When I used my [device] at the very moment I became concerned … … about whether the [device] will really perform as well as it is supposed to. … about how really reliable the [device] will be. … that the [device] will not provide the level of benefits I was expecting.	adapted from Stone and Grønhaug (1993)	.906
Security risk	When I used my [device] at the very moment I became concerned … … about the security of my transaction. … making use of payment with my [device]. … that the information I provided would not be manipulated by inappropriate parties. … that inappropriate parties may store the information I provided. … that the information I provided would not be exposed to inappropriate parties. … about the security of financial transactions via my [device]. … that the transmission of data over my [device] was unsafe. … that information on my [device] will be delivered to the wrong persons.	adapted from Hubert et al. (2017)	.933
Purchase intention	Please evaluate your purchase intention at the very moment with your [device]: Unlikely to likely. Definitely not to definitely. Improbable to probable.	adapted from Hubert et al. (2017)	.904
Habit	Shopping with my [device] has become a habit for me. I am addicted to using my [device] for shopping. I must use my [device] for shopping. Shopping with my [device] has become natural to me.	adapted from Venkatesh et al. (2012)	.690
Ease of use	Learning how to shop with my [device] was easy for me. I found it easy to do what I wanted to do with my [device]. It was easy for me to become skillful at shopping with my [device]. I found it easy to shop with my [device].	adapted from Hubert et al. (2017)	.879
Usefulness	Shopping with my [device] improves my performance regarding my shopping tasks. Shopping with my [device] improves my productivity. I find that shopping with my [device] is convenient. Shopping with my [device] enhances my effectiveness in my shopping tasks.	adapted from Hubert et al. (2017)	.870

et al., 2016; Brock et al., 2013). Additionally, the replication reveals that the measurement properties of website design were inadequate, questioning the general applicability of adapted scales from the e-commerce context (e.g., Parasuraman et al., 2005; Vlachos et al., 2011). Thereby, it is indicated that mobile retailers have to employ different design elements on mobile stores than on product web pages (Bleier et al., 2019) to induce effective customer experiences.

Hence, the robustness of previously published insights about ESQ in MSQ research is questioned. This conclusion indicates that a varied set of factors which are very different from the electronic marketing approach impact customer preferences (Kumar, 2018). Consequently, there is a need for further scale development, providing comprehensive measurements for MSQ attributes and dimensions by using different methodological approaches (Adams et al., 1992; Blut et al., 2018).

Research question 2. *With regard to the ubiquity of services, which is the right device based on location and time to reach a customer?*

Basically, this research reveals that mobile device users generally obtain a higher purchase intention as well as a higher willingness to pay compared to their desktop counterpart, although mobile device users perceive significantly higher security and performance risks. Hence, the results support the assumption that contextual factors offer such an advantage for mobile device users that even significantly higher risks are accepted (de Haan et al., 2018; Kumar, 2018; Venkatesh et al., 2017; Xu et al., 2017). According to the TAM (Davis, 1989), mobile devices seem to induce higher perceptions of ease of use and usefulness for shopping purposes, which in turn effect shopping trip intentions more positively (Hubert et al., 2017). However, these advantageous perceptions are linked to contextual boundary conditions.

Table 6
Differences between mobile and desktop device users (Study 2).

Construct	Device group	Mean	Δ	t
Performance risk	Mobile device	2.623	.766**	8.681
	Desktop device	1.857		
Security risk	Mobile device	3.138	.253**	3.138
	Desktop device	2.885		
Financial risk	Mobile device	3.003	.072$^{n.s.}$	0.939
	Desktop device	2.931		
Purchase intention	Mobile device	3.538	.194**	2.445
	Desktop device	3.344		
Willingness to pay (€)	Mobile device	82.39	9.05**	3.214
	Desktop device	73.34		

With regard to temporal boundary conditions, no interaction effects between the time of the day and device are found. Hence, according to the construal level theory (Trope and Liberman, 2010), mobile device users and desktop device users seem to form similar mental construal with regard to the temporal distance. Consequently, their shopping trip intentions are equally impacted by the contextual factor time.

With regard to spatial boundary conditions, interaction effects between the location of the user and the device are found, but in the contrary direction than expected. Mobile device users do not intend to purchase more frequently on the way, but at home. Hence, according to the construal level theory (Trope and Liberman, 2010), mobile device users are not able to form concrete mental construal on the way, decreasing their purchase intention compared to desktop device users. There is evidence in the results that increased perceptions of financial and performance risks are responsible for this circumstance. Consequently, if a customer is at home, he has to be reached on a mobile device, since he obtains significantly higher purchase intentions at this location and his risk perceptions are at the lowest level.

5.2. Managerial implications

Based on the results presented, managers are encouraged to apply a customer-centric approach in organizing their marketing practices around distinct customer groups (in this context mobile device users and

Table 7
Interactional effect of location on risk perceptions and shopping trip intentions.

	Shopping trip intentions				Risk perceptions					
	Willingness to pay (€)		Purchase intention		Performance risk		Security risk		Financial risk	
	At home	On the way	At home	On the way	At home	On the way	At home	On the way	At home	On the way
Mobile device user	83.25	80.25	3.642	3.280	2.507	2.908	3.051	3.353	2.901	3.256
Desktop device user	73.40	73.15	3.342	3.348	1.866	1.831	2.897	2 .850	2.945	2.931
Device	F = 7.063	p < .01	F = 1.679	n.s.	F = 75.071	p < .01	F = 13.137	p < .01	F = 3.523	n.s.
Location	F = .260	n.s.	F = 3.971	p < .05	F = 3.417	n.s.	F = 1.974	n.s.	F = 2.901	n.s.
Device*location	F = .186	n.s.	F = 4.228	p < .05	F = 4.815	p < .05	F = 3.716	n.s.	F = 5.692	p < .05

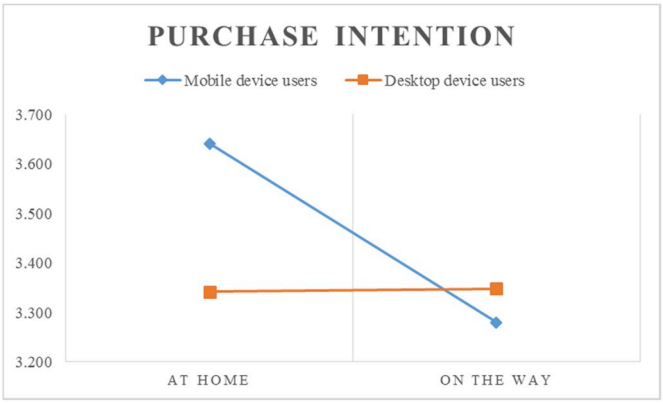

Fig. 5. The interaction effect between device users and location on the purchase intention.

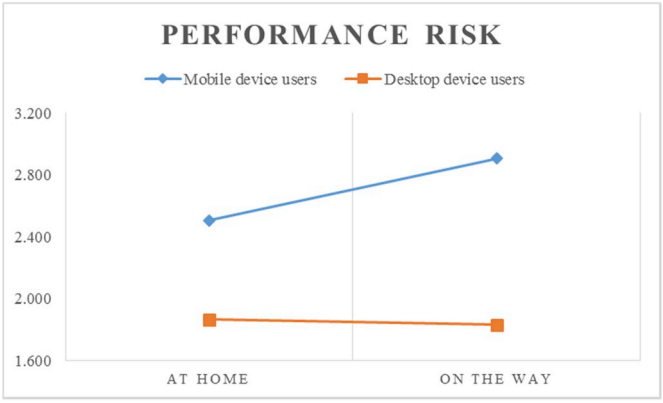

Fig. 6. The interaction effect between device users and location on the perceptions of performance risk.

desktop device users) rather than product categories (Althuizen, 2018; Crecelius et al., 2019). This implication is based on contextual boundary conditions. For instance, with regard to the contextual factor time, managers are advised not to adopt a customer-centric approach when designing a time-based offering. In contrast, with regard to the contextual factor location, managers are encouraged to induce device switching from a more static device to a more mobile device when customers are at home (Xu et al., 2017).

But, the expectation that mobile devices will particularly transform the spatial dimension of retailing has not been confirmed by the results (especially H7). Moreover, they confirm recent problems of mobile commerce encompassing decreased purchase intentions, lower conversion rates (de Haan et al., 2018; Kaatz et al., 2019), and higher shopping cart abandonment rates (Huang et al., 2018) compared to the desktop counterpart. Thus, this indicates that many retailers are still struggling to deliver satisfying levels of MSQ. This is particularly critical in the

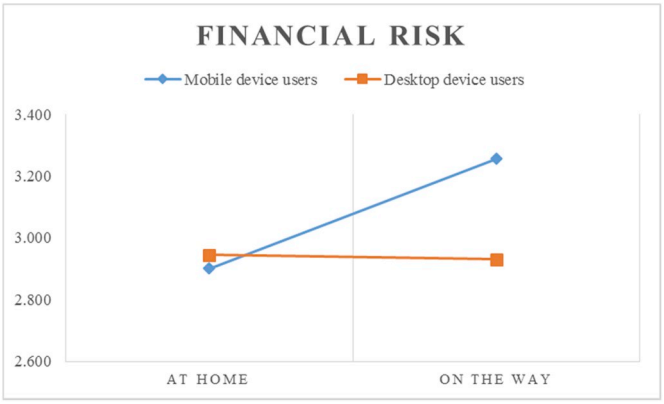

Fig. 7. The interaction effect between device users and location on the perceptions of financial risk.

context of perceived service quality, since service failures have a long-term negative effect on perceptions of service quality despite recovery efforts (Gijsenberg et al., 2015). Based on the results presented, retailers are encouraged to implement an upmarket repositioning strategy, particularly increasing levels of MSQ (Lee et al., 2018). It can be argued that retailers need to adapt their existing concepts of marketing strategies to the characteristics of mobile commerce, particularly redefining practices of ESQ and handling mobile device users as a distinct customer group (Althuizen, 2018; Crecelius et al., 2019). In order to create effective mobile customer experiences and satisfying levels of MSQ, retailers are encouraged to eliminate potential techno-stressors (Tarafdar et al., 2019) by reducing the perceived risks of their mobile store with regard to the following implications.

Performance risk. Since mobile devices are related to screen-size constraints (Ghose et al., 2013; Xu et al., 2017), which may be causing cognitive overload during the purchase process (Ghose et al., 2013), retailers are encouraged to reduce clicks to purchase to a minimum. In this context, retailers should provide an infrastructure of their mobile store that supports the digital content (Bleier et al., 2019), for instance by implementing a responsive design for the mobile store and ensuring the synchronicity of its hyperlinks (Kaatz et al., 2017).

Security risk and financial risk. Since contextual value is generated by marketing activities based on personalization and the location of the customer, customers are even more afraid of losing control of their personal data (de Haan et al., 2018; Hubert et al., 2017). First, retailers are advised to communicate their security processes prior to purchase, particularly in case of losing the connection during the payment process. Second, retailers are advised to implement convenient payment methods, such as one-click checkouts. Conclusively, Fig. 8 summarizes the contributions and implications.

5.3. Limitations and further research

This research has several limitations that could be addressed in future research. For both studies, although the questionnaires were

Table 8
Interactional effect of time of the day on risk perceptions and shopping trip intentions.

	Shopping trip intentions				Risk perceptions					
	Willingness to pay (€)		Purchase intention		Performance risk		Security risk		Financial risk	
	Working hours	Leisure hours	Working hours	Leisure hours	Working hours	Leisure hours	Working hours	Leisure hours	Working hours	Leisure hours
Mobile device user	83.78	80.98	3.488	3.589	2.677	2.567	3.206	3.068	3.023	2.983
Desktop device user	73.73	72.97	3.354	3.334	1.890	1.826	2.887	2 .883	2.913	2.947
Device	$F = 10.244$	$p < .01$	$F = 5.979$	$p < .05$	$F = 74.937$	$p < .01$	$F = 9.781$	$p < .01$	$F = .886$	n.s.
Time of the day	$F = .398$	n.s.	$F = .267$	n.s.	$F = .967$	n.s.	$F = .782$	n.s.	$F = .002$	n.s.
Device*time of the day	$F = .129$	n.s.	$F = .582$	n.s.	$F = .070$	n.s.	$F = .702$	n.s.	$F = .224$	n.s.

designed to avoid common method bias, it is impossible to address common method bias in single-informant studies (Guide and Ketokovi, 2015). Hence, future studies are advised to use multiple data sources to reduce the risk of common method bias. Furthermore, the studies used self-reported measures for the outcomes. Although this procedure is common in marketing literature for examining the consequences of the construct of interest (e.g., Blut, 2016; Parasuraman et al., 1988; Parasuraman et al., 2005; Wolfinbarger and Gilly, 2003), further research would benefit from using actual spending behavior (e.g., Grewal et al., 2018).

With regard to the replication study, a student sample was used. Although a homogeneous sample is needed to account for internal validity (Calder et al., 1981; Kardes, 1996), future research is encouraged to use a heterogeneous sample to account for external validity. Additionally, the replication study was validated in one country only, Germany. Since Blut et al. (2015) demonstrate that country culture influences perceptions of service quality differently, future research could repeat the replication in different country settings.

With regard to the contextual factors study, it is only valid for one product category. Future research is encouraged to replicate the results in other product categories. As a limitation of the method, participants were asked to go through the entire purchase process at one moment. Future research examining this topic should be capable of encompassing the whole path to purchase across various devices and several days, such as the diary method (e.g., Smith et al., 2003).

Additionally, the results of Study 2 were interpreted as negative influences of stressors triggered by mobile devices (techno-distress). According to Tarafdar et al. (2019), it is possible that mobile device users also feel positive stress when shopping with mobile devices (techno-eustress), motivating them to master challenges in a positive way. Thus, future research is encouraged to examine the negative impact of ubiquity on purchase intentions and risk perceptions in the context of techno-stressors.

Finally, as customers' perceptions of security and financial risk stated, retailers face the challenge of building private relationships with virtually no personal information on customers to reveal (e.g., Kumar, 2018; Schreiner et al., 2019). Thus future research is advised to examine the trade-off between privacy and personalization (Marketing Science Institute, 2018).

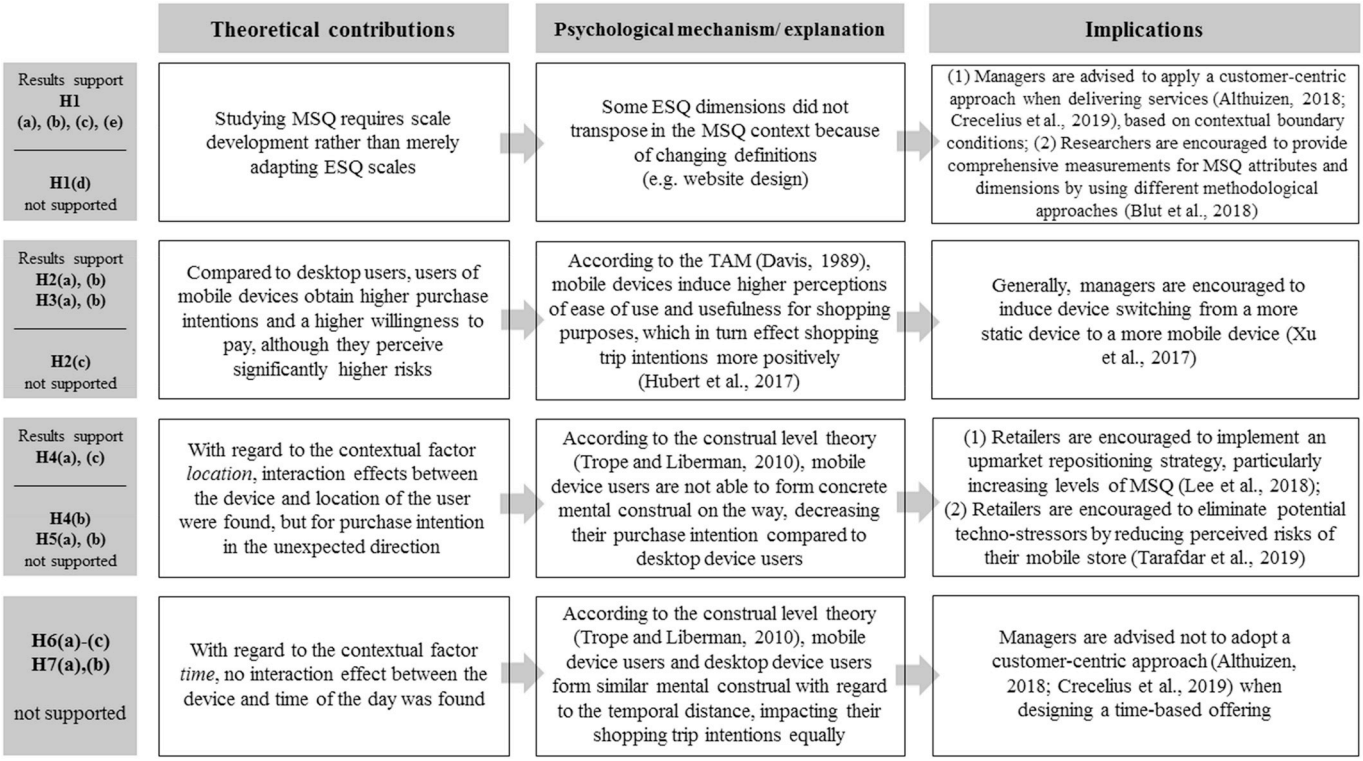

Fig. 8. Summary of the contributions and implications derived from the results.

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